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The Nexus of Energy and Health:
A Systems Analysis of Costs and Benefits of Ozone Control by Activated Carbon Filtration in Buildings

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The Nexus of Energy and Health:
A Systems Analysis of Costs and Benefits of Ozone Control by Activated Carbon Filtration in Buildings

by

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Dedication

To Vanessa, my best friend and wingman for life.

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The Nexus of Energy and Health:
A Systems Analysis of Costs and Benefits of Ozone Control by Activated Carbon Filtration in Buildings

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Americans spend nearly 90% of their lifetimes indoors, where they receive 50-70% of their exposure to ozone. The US EPA has designated ozone as a hazardous air pollutant and ozone exposure has been linked to respiratory mortality, hospital admissions, restricted activity days, and school loss days. In addition, the most susceptible populations to ozone exposure are children and the elderly, especially if they suffer from an existing respiratory health condition.

One possible solution to reduce indoor ozone exposure is to use activated carbon filtration in a building's heating, ventilation, and air conditioning (HVAC) system. In many cases, using commercially available activated carbon filters will have minimal additional capital and energy costs in comparison to standard particle filters.

A complex systems model for evaluating the potential costs and benefits of ozone control by activated carbon filtration in buildings was developed as part of this dissertation. The modeling effort included the prediction of indoor ozone concentrations

and exposure with and without activated carbon filtration. As example applications, the model was used to predict benefit-to-cost ratios for commercial office buildings, long-term healthcare facilities, K-12 schools, and single-family homes in 12 American cities in five different climate zones. Health outcomes due to reduced indoor ozone exposure were determined using the USEPA methodology for outdoor ozone exposure, which includes city-specific age demographics and disease prevalence. Health benefits were evaluated using disability-adjusted life-years, which were then converted to a monetary value to compare with activated carbon filtration costs.

Modeling results indicate that activated carbon filtration during the summer ozone season should be beneficial and economically feasible in commercial office buildings, long-term healthcare facilities, and K-12 schools. The benefits of activated carbon filtration in single-family homes are predicted to be marginal, except for sensitive populations or in cities with high seasonal ozone and high air conditioning usage.

Field experiments of activated carbon filters in an operational university laboratory resulted in an average ozone single-pass removal efficiency of 70%. An additional benefit-cost analysis of activated carbon filtration in the laboratory showed that ozone-related health costs were reduced by 62% and fan energy costs were reduced by 21% compared to a baseline condition. Finally, the field study demonstrated that activated carbon filtration for ozone removal could be economically beneficial in buildings with very high ventilation due to reductions in health, energy, and filter replacement and installation costs.

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1. INTRODUCTION

1.1. The Issue

Exposure to ozone and ozone reaction products is harmful to human health. Ozone reacts with polyunsaturated fatty acids in fluids lining the lung with subsequent adverse effects in the airway epithelium (Levy et al., 2001). Several researchers have shown a link between exposure to ozone and premature mortality (Bell et al., 2005; Ito et al., 2005; Jerrett et al., 2009; Levy et al., 2005; Smith et al., 2009; USEPA, 2006, and references provided therein). Additionally, there have been several studies that associate ozone exposure and increases in respiratory-related hospital admissions (e.g., Burnett et al., 1999), minor restricted activity days (e.g., Ostro and Rothschild, 1989), and school loss days (e.g., Chen et al., 2000). In a recent analysis, the USEPA estimates that 265 to 450 lives will be saved each year in the United States by reducing the eight-hour ozone standard by 5 parts per billion (ppb), resulting in potential health benefits of U.S. $7.5B to $15B (2011 dollars) per year (USEPA, 2014a).

Nearly 1/3 of Americans live and work in counties with ozone concentrations that exceed the primary eight-hour average National Ambient Air Quality Standard (NAAQS) for ozone (USEPA, 2014b). The NAAQS for ozone is meant to protect public health, including the health of sensitive populations such as children, people with asthma, and the elderly. Ozone concentrations are typically lower indoors than outdoors, largely due to its reaction with materials in the building envelope, heating, ventilating, and air conditioning (HVAC) system components, building contents, and occupied space (Chen et al., 2012a; Fadeyi, 2014; Fadeyi et al., 2013; Fadeyi et al., 2009; Morrison et al., 1998; Stephens et al., 2012; Wang and Morrison, 2010; Wang and Morrison, 2006; Weschler, 2000). Although ozone concentrations are typically lower indoors than outdoors, Americans spend an average of nearly 90% of their time indoors (Klepeis et al., 2001). This leads to the indoor environment being important with respect to total inhalation exposure to ozone. For example, in a study involving 2,500 residences in seven cities, indoor exposure accounted for 43% to 76% of total daily exposure to ozone, with a mean of 60% (Weschler, 2006). As such, ozone control in buildings should be further explored.

1.2. Dissertation Objectives

The overall goal of the dissertation is to evaluate the potential health benefits of installing MERV-rated combination activated carbon filters in a diverse set of building environments, including homes, office buildings, healthcare facilities, and schools. A sample of cities from all climate zones in the U.S. will be used to predict the benefits and costs of filtration in each climate zone. The health benefits will be evaluated using disability-adjusted life-years (DALYs), which are a metric used to calculate disease burden and include factors for years lost to premature mortality and years lost due to disability per disease incidence. DALYs can also be used to estimate monetary health costs and benefits due to pollutant exposure. Capital and operating costs of combined activated-carbon filters will be investigated by reviewing the scientific literature, manufacturer filter specifications, and local HVAC operational characteristics and utility rates.

Primary research questions include the following:

1. Is there a net benefit (cost vs. health improvement) in utilizing in-duct activated carbon filters in heating, ventilation, and air-conditioning (HVAC) systems in commercial and residential buildings? If so, are there parameter thresholds above which benefits are greater than costs?
2. Will in-duct activated carbon filters in HVAC systems significantly reduce indoor chemical reactions in office and residential buildings? If so, how can this be quantified, and by how much?
3. Can modeling results be verified by sampling in realistic indoor environments?

The four primary research objectives are identified below:

1. Complete a detailed literature review related to ozone removal by activated carbon, indoor ozone chemistry, and health metrics related to ozone and its reaction products.
2. Develop a systems model that can predict the net benefit of utilizing in-duct activated carbon filters in HVAC systems, and apply the model to realistic scenarios in different climate zones in residential and commercial indoor environments.
3. Test the single-pass removal efficiency for ozone through common residential activated carbon filters under realistic operating conditions.

4. Develop strategies and policies to use activated carbon filters during periods of high outdoor ozone concentrations.

1.3. Scope of Research

This study focuses only on in-duct activated carbon filters for ozone control. Other control media and portable air purifiers were not considered. A mass balance model was used to estimate indoor ozone and ozone reaction products with and without activated carbon filtration. The mass balance model was based on assumptions of steady-state and well-mixed conditions. A limitation of the model was that it did not capture peak ozone events, rather, average indoor ozone was estimated for the summer ozone season in order to estimate exposure in accordance with the methodology applied by the United States Environmental Protection Agency (USEPA). The model was applied across multiple cities and climate zones in the United States using standardized building sets and did not incorporate a distribution of the building stock in each city.

Health benefits were determined using disability-adjusted life-years (DALY), which is a metric used by health organizations such as the World Health Organization (WHO) to determine the burden of disease across a large population. One DALY is equivalent to one lost year of healthy life and includes years of life lost to mortality and morbidity applied across a population of 100,000 or more.

The focus of this study involves applications of a systems model as opposed to a major field campaign. However, field-testing of residential activated carbon filters using an HVAC test rig was completed as part of this dissertation.

1.4. Major Components and Connections of the Dissertation

An illustration showing the major components and connections of the dissertation is presented in Figure 1. The literature review included a review of the published literature on activated carbon filtration for ozone removal, indoor chemistry, the health outcomes of ozone exposure, and energy and filtration control costs (link A). The connection between the literature review and sub-models (link A) also included an extensive review of currently available carbon filter products via phone interviews with major filter manufacturers. The published and grey literature (including government reports and data) was also reviewed for the model development (link B) and model applications (link C). Additionally, a review of the published literature on activated carbon filter performance, indoor chemistry, energy and control costs, and building operation were completed for the field study and laboratory experiments (links D and E, respectively). Finally, the systems model was used in connection with the field study and laboratory experiments to estimate the economic costs and benefits of activated carbon filtration in buildings using filter performance metrics measured in the field or laboratory – these connections are displayed with the dashed arrows in Figure 1.

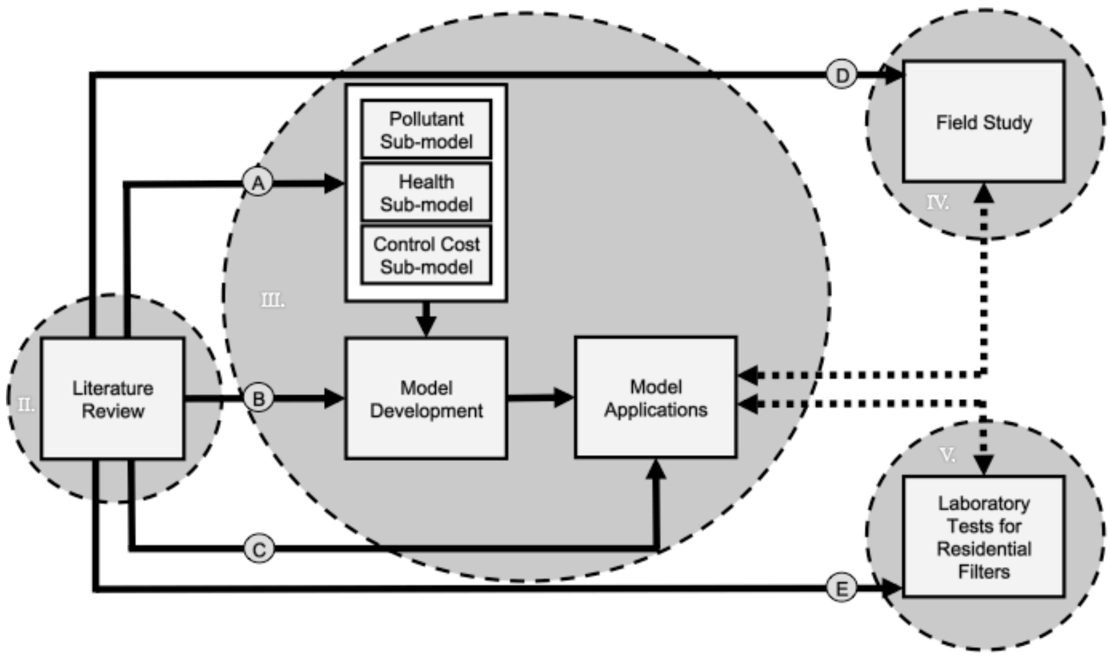

Figure 1. Major components and connections of the dissertation. Roman numerals represent the respective dissertation chapter of each major component. The size of each chapter "sphere" represents the relative amount of time spent on development, planning, and execution.

As a result of this dissertation research, four journal papers are in review or development. A list of the journal papers is presented below.

Journal papers in review or development:

1. Aldred, J., Darling, E., Siegel, J., Morrison, G., Corsi, R. (2015). Benefit-cost analysis of commercially available activated carbon filters for indoor ozone removal in residential buildings. Submitted to *Indoor Air*.

2. Aldred, J., Darling, E., Siegel, J., Morrison, G., Corsi, R. (2015). Cost-benefit analysis of commercially available activated carbon filters for indoor ozone removal in buildings. Submitted to *Science and Technology for the Built Environment*.

3. Aldred J., Crain, N., Corsi, R., Novoselac, A. (2015). A benefit-cost analysis of reduced ventilation and carbon filtration in a university laboratory building. Submitted to *Building and Environment.*

4. Aldred, J., Crain, N., Corsi, R. (2015). Scale testing of commercially available residential activated carbon filters for ozone control. In development.

Additionally, four conference papers were also presented based on this dissertation research. A list of the conference papers is presented below.

Conference papers presented:

1. Aldred, J., Corsi, R.L., Novoselac, A. (2014). Benefit-Cost Analysis of Reduced Ventilation in a University Laboratory Building. *The 2014 University of Texas Sustainability Symposium*.

2. Aldred, J., Corsi, R.L. (2014). A method to estimate the health benefits of activated carbon filtration. *Indoor Air 2014: Proceedings of the 13th International Conference on Indoor Air and Climate*, paper ID 711.

3. Aldred, J., Darling, E., Corsi, R.L. (2014). A benefit-cost analysis of activated carbon filtration in long-term healthcare facilities. *Indoor Air 2014: Proceedings of the 13th International Conference on Indoor Air and Climate*, paper ID 714.

4. Aldred, J., Jackson, M., Corsi, R.L. (2014). A method to estimate the health benefits of MERV-rated activated carbon filtration. *Indoor Air 2014: Proceedings of the 13th International Conference on Indoor Air and Climate*, paper ID 913.

1.5. Outline of Dissertation

Background information on indoor ozone chemistry, health effects, and economic metrics is provided in Chapter 2. The background information includes a discussion of the effects of ozone and ozone reaction products in buildings, the effectiveness of activated carbon filters for indoor ozone removal, and the potential health effects of exposure to ozone and ozone reaction products such as secondary organic aerosols, formaldehyde, and acetaldehyde. The derivation of the integrated systems model and the modeling results are described in detail in Chapter 3. Methods and results of the field study experiments are discussed in Chapter 4. Methods and results of the filter testing experiments are discussed in Chapter 5. Major research findings and related conclusions are provided in Chapter 6. Appendices A and B provide in depth methodology of the integrated systems model and the results of applications in single-family homes (Appendix A) and commercial buildings (Appendix B). Appendix C provides a detailed energy and benefit-cost analysis of carbon filtration in an operational university laboratory. The programming code used for the Monte Carlo simulation in Appendix A is presented in Appendix D.

2. LITERATURE REVIEW

Elements of this background section are taken from a draft report of ASHRAE Research Project 1491, of which I am a co-author. I am the author of all text taken from the ASHRAE report.

2.1. The Role of Activated Carbon Filters in Public Health

In the United States, average outdoor ozone concentrations decreased nationally by 28% between 1980 and 2010, and by approximately a factor of two during the same period in some air basins such as in the South Coast Air Quality Management District of Southern California (SCAQMD, 2013; USEPA, 2012a). However, population trends have involved a large migration from colder regions of the country to areas with a high operational usage of central air conditioning and heating. In fact, during the past year eight of the 15 fastest growing cities were in the state of Texas and 14 of the 15 fastest growing cities were in the south and southeast regions of the U.S. (US Census Bureau, 2013). The combination of increasing migration to warmer climates, the potential for higher atmospheric temperatures due to climate change, and higher urban emissions of ozone precursors such as NO_X and biogenic VOCs will ultimately result in higher ozone concentrations in growing cities.

Climate change will lead to greater use of central HVAC systems in many buildings, as well as a greater time of exposure to pollutants in indoor environments. Activated carbon filters in HVAC systems have been shown to effectively remove ozone from indoor environments during sustained operation and may lead to significant reductions in mortality, hospital admissions, asthma exacerbations, and school and work loss days when utilized in urban areas with high ambient ozone.

2.2. Impact on Health

Previous studies have suggested that building related symptoms are responsible for a 3-4% reduction in office productivity, which is roughly equal to $50 billion (1997 $USD) in economic losses per year in the United States (Fisk and Rosenfeld, 1997). Apte et al. (2008) used survey data and measurements from the Building Assessment Survey and Evaluation (BASE) study on commercial buildings to compare concentrations of indoor pollutants versus symptoms of building related sickness (BRS). All BRS symptoms increased with increases in outdoor ozone concentration with the exception of "dry skin." Increased BRS symptom reporting was closely tied to late afternoons when the ambient ozone concentrations were highest. Higher indoor concentrations of formaldehyde, acetaldehyde, pentanal, hexanal, and nonanal were observed to correlate with higher ambient ozone concentrations, suggesting that ozone chemistry is an important source of these reaction products in office buildings. Due to the economic impact of ozone-related BRS symptoms in commercial office buildings—and the less well-known economic impact of ozone exposure in homes, schools, and other buildings—further research is warranted on the health impacts caused by exposure to these harmful pollutants.

2.2.1. Health Effects of Ozone

Exposure to ambient ozone concentrations initiates cellular damage to lung tissue, specifically through reactions with polyunsaturated fatty acids (PUFA), amino acid proteins, and some low-molecular weight compounds such as glutathione, urate, vitamins C and E, and free amino acids (USEPA, 2006; and references therein). Previous studies have shown that ozone does not typically penetrate the epithelial lining fluid (ELF) in the lungs (USEPA, 2006; and references therein). However, the ELF varies in thickness, which may allow ozone to diffuse through the ELF and react with cellular membranes if the ELF is less than 0.1 μm thick (USEPA, 2006; and references therein).

Ozone reactions with epithelial cells lead to the formation of by-products that are similar or identical to those formed when ozone reacts with many indoor surfaces, e.g., reactive ozonides, aldehydes, and hydroperoxides (USEPA, 2006; and references therein). The ozonation of PUFAs in rat lung tissue led to the formation of nonanal and hexanal at 220 ppb of ozone (USEPA, 2006; and references therein). Ozone reactions with PUFAs in human lung tissue leads to the formation of heptanal, hexanal, and nonanal (USEPA, 2006; and references therein). Importantly, previous studies have shown that rats are much more resilient to ozone exposure than humans (USEPA, 2006; and references therein).

The human lung has natural controls that balance the bidirectional flow of fluids and cells between the air and blood compartments. Exposure to ozone can upset this balance, leading to lung inflammation and increased permeability of the ELF. Inflammation is caused by ozone reactions with antioxidants and unsaturated lipids in the ELF. The resulting chemical by-products and inflammation facilitate changes in cell membranes and allow increased mass transport from lung air to the blood stream causing increased permeability of the ELF. This in turn can lead to higher exposure to co-pollutants (VOCs, particulate matter) passing through the ELF and into the blood stream (USEPA, 2006; and references therein).

Increased ozone exposure has been linked to premature mortality. Several research teams have analyzed data from the National Morbidity and Mortality Air Pollution Study (NMMAPS), which evaluated air pollution and health data from the largest 98 cities in the United States from 1987-2000. Bell et al. (2005) found a 0.87% increase in premature mortality per 10 ppb increase in average daily ozone concentration, and a 0.35% increase in mortality related to a 10 ppb increase in the one-hour daily maximum ozone concentration within 0-2 days of the exposure incident. Ito et al. (2005) predicted a 0.39% increase in premature mortality per 10 ppb increase in one-hour daily maximum ozone and included seasonal factors, temperature, and use of air conditioning in their meta-analysis. Ito et al. (2005) found an increased mortality risk due to ozone during the summer periods when ambient ozone is highest. Bell et al. (2006) developed an exposure-response curve from the NMMAPS dataset for ozone indicating a strong link between ozone exposure and premature mortality, even at low concentrations. Thurston and Ito (2001) evaluated time-dependent exposure to ozone and found that many previous studies had underestimated ozone mortality. Jerrett et al. (2009) utilized mortality data from the American Cancer Society Cancer Prevention Study (448,850 participants, 188,777 deaths after 18-year follow-up) and USEPA monitoring data for ambient ozone and $PM_{2.5}$ for 96 US metropolitan areas to develop an exposure-response curve for ozone concentration and mortality. They observed that for every 10 ppb increase in one-hour daily maximum ozone, the risk of death from respiratory causes increased 2.9% in single-pollutant models (ozone only).

Additional researchers have studied the association between increased ozone concentrations and mortality, including same day versus lagged effects. Levy et al. (2005) projected a 0.41% increase in mortality per 10 ppb increase in one-hour daily maximum ozone concentration by evaluating 48 city-specific research studies on ozone-related mortality. Their study revealed that same day effects were larger than lagged effects per ozone incident. Parodi et al. (2005) observed that the variance in the ozone-mortality relationship depends on the lag time after the ozone incident (0 to 2 days) with the highest association with mortality one day after the ozone incident. Zhang et al. (2006) observed an increase of 0.45% in all-cause mortality per 5 ppb increase in eight-hour ozone after a one-day lag for all ages and seasons in Shanghai, China. They found an increase of 0.53% for cardiovascular mortality and 0.35% for respiratory related mortality per 5 ppb increase in eight-hour ozone concentration for all seasons.

Seasonal effects of ozone exposure on mortality have also been studied. Kim et al. (2004) determined an increase in mortality risk (Relative Risk ratio = RR = 1.0336) for all seasons due to ozone exposure by assuming a threshold concentration of ozone of 27.61 ppb. Their study utilized four years of ambient ozone and mortality data from Seoul, South Korea. Gryparis et al. (2004) evaluated mortality and ozone data from 23 European cities and found an increase of 0.33% in mortality per 5 ppb increase in one-hour daily maximum ozone concentration during the summer. They also observed an increase in all-cause mortality of 0.34% for a 5 ppb increase in two-day average maximum eight-hour ozone concentration. Parodi et al. (2005) observed an increase in mortality for all ages and all seasons varying from 1.4-2.4% per 25 ppb increase in one-hour daily maximum ozone concentration in Genoa, Italy.

An association appears to exist between window air conditioning (AC) units and increased ozone related mortality, perhaps due to higher air exchange rates in older homes with these units (Smith et al., 2009). Smith et al. (2009) completed a detailed meta-analysis of the NMMAPs data including daily temperature, dew point, PM_{10} and $PM_{2.5}$, hourly and daily values for ambient ozone concentrations for 79 of the 98 NMMAPs cities. They also considered window air conditioning and central air conditioning as two different types of air conditioning rather than merging both types of AC as had been done in previous studies, e.g., Bell and Dominici (2008).

Ozone exposure has also been linked to morbidity, especially respiratory related illnesses. Mudway and Kelly (2004) developed a linear relationship between ozone exposure and lung inflammation and airway responses. Brown et al. (2008) and Adams et al. (2006) linked ozone exposure to decreased pulmonary function and gas exchange in the respiratory system. McDonnell et al. (1999) observed an increased risk in asthma diagnoses for males (RR = 2.09, 95% CI = 1.03 to 4.16) for a 27 ppb increase in ambient ozone concentration. Glad et al. (2012) observed a 2.5% increase in asthma related emergency department (ED) visits per 10 ppb increase in one-hour maximum ozone two days following the ozone incident. They observed that the strongest association for ER visits was four days after the ozone incident. Anderson et al. (1997) observed that an increase in eight-hour ozone concentration of 25 ppb led to an increase of 4.0% in hospital admissions for chronic obstructive pulmonary disease (COPD) in six European cities (lagged 1-3 days).

Increases in ozone concentration and exposure are known to have adverse effects on children. McConnell et al. (2002) linked ozone exposure to increased asthma diagnoses among children in a southern California cohort of 3,535 children, especially among children who played multiple sports outdoors. Tager et al. (2005) related lifetime ozone exposure to decreased measures of airway function in a cohort of California adolescents. Yang et al. (2003) associated increased ozone exposure of approximately 10 ppb with increased visits to hospital emergency rooms (ER) for both children (RR = 1.22, 95% CI = 1.15 to 1.30) and the elderly (RR = 1.13, 95% CI = 1.09 to 1.18) in a Vancouver, British Columbia cohort. Increases in ozone exposure have also been linked to minor restricted activity days (MRADs) and increased school absences (Hubbell et al., 2005).

Ozone has been found to be a surrogate for increased personal exposure to $PM_{2.5}$, especially during the summer (Sarnat et al., 2001 and 2005). Increased $PM_{2.5}$ exposure has its own inherent health risks and has been linked to increased mortality due to lung cancer and cardiovascular disease (Pope et al., 2011). The correlation between ozone and increased $PM_{2.5}$ can be explained in-part by the formation of outdoor secondary organic aerosols. Secondary organic aerosols can also be rapidly formed indoors following reactions between ozone and terpenoids from scenting agents, cleaners, and other sources.

The studies described above involved health impacts associated with outdoor ozone concentration measurements. But the average American spends over 70 years of their lifetime in indoor environments (based on Klepeis et al., 2001), where concentrations of ozone increase to some extent when outdoor ozone concentrations increase. And while indoor ozone concentrations are generally much lower than outdoor concentrations, nearly half of personal exposure to ozone of outdoor origin takes place indoors (Weschler, 2006 and references therein). Furthermore, indoor environments facilitate chemical reactions between ozone and indoor materials, as well as ozone and a wide range of reactive terpenoids that exist in indoor air at higher concentrations than in outdoor air (Hodgson and Levin, 2003; Weschler, 2000). The by-products of these reactions often have higher concentrations indoors than outdoors and may be harmful to human health (Weschler, 2006). Therefore, *the indoor and outdoor environments are undeniably linked, and efforts to remove ozone of outdoor origin from buildings should dramatically reduce population exposures to ozone and its reaction products.*

Chen et al. (2012a) recently completed seminal work that links short-term mortality with indoor ozone exposure. Human activity patterns were referenced from the National Human Activity Pattern Survey (NHAPS; see Klepeis et al., 2001) and ozone mortality data from Bell et al. (2004) were used for 24-hour ozone concentration. Ozone mortality data for one-hour and eight-hour ozone concentrations were taken from Smith et al. (2009). A mass balance model was developed and included residential air exchange rates from Persily et al. (2010) and an assumed ozone decay rate due to reactions with surfaces of 3/hr. Chen et al. (2012a) also accounted for changes in air exchange rate by opening windows, an action which leads to higher concentrations of indoor ozone and a potential for higher mortality rates. The mass balance model included the fraction of homes per city with air conditioning, and the fraction of time that air conditioning was operating per city. Chen et al. (2012a) developed several linear regressions between air exchange rate and ozone mortality, as well as ozone exposure coefficient and ozone mortality for 18 of the NMMAPS cities. The strongest linear association was between ozone exposure coefficient and mortality for one-hour daily maximum ozone for 18 cities.

Several researchers have evaluated the health benefits of attaining lower ambient ozone standards nationwide using the willingness-to-pay method. Hubbell et al. (2005) generated estimates of average ozone concentrations for every county in the United States using spatial interpolation. Their study incorporated a Monte Carlo analysis to link average ozone concentration to premature mortality and increased asthma and respiratory health incidents. Results of their study indicate that achieving an 80 ppb ambient ozone limit nationwide would prevent 840 mortalities nationwide and result in $6.6B (2012 US$) in health benefits due to decreased mortality and hospital admissions. In a similar study, Berman et al. (2012) estimated that more than 1,000 premature mortalities could be prevented each year in the United States by attaining the 75 ppb ambient ozone standard nationwide.

2.2.2. Health Effects of Gaseous Reaction Products

Ozone engages in both heterogeneous and homogeneous reactions that lead to the formation of a broad spectrum of reaction products. Reaction products include hydroxyl radicals and other radical species, formaldehyde, acetaldehyde, C_3 to C_{10} saturated and unsaturated aldehydes, light monoketones, dicarbonyls, mono- and dicarboxylic acids, and secondary organic aerosols (SOA) (e.g., Anderson et al., 2012a and 2012b; Sarwar and Corsi, 2007; Weschler, 2006; Sarwar et al., 2003).

Ozone reaction products have been linked to increases in airway irritation and decreases in respiratory function (Anderson et al. 2007). Wolkoff et al. (1999 and 2000) found that respiratory rates in mice decreased by up to 30% and 50% when exposed to mixtures of ozone and α-pinene or isoprene, respectively. Wolkoff et al. (2008) observed a greater than 30% reduction of mean respiratory frequency in mice exposed to d-limonene/ozone mixtures for 30 minutes. They noted that the secondary endo-ozonide of limonene is similar to ozonides associated with lung surfactants, compounds potentially causative of pulmonary effects. But while sensory irritation and air flow limitations in mice are clearly evident during exposure to d-limonene/ozone mixtures, repeated exposures over a 10-day period did not lead to inflammation of the respiratory tract (Wolkoff et al., 2012).

Rohr et al. (2003a) studied the effects of ozone/isoprene reaction products on six murine strains of mice. Sensory irritation was observed in the form of reduced respiratory frequency and peak expiratory volume/tidal volume. The products that caused these effects, e.g., specific gaseous products or ultrafine particles, were not studied. Variations in results between murine strains may indicate genetic variability in human populations as well.

Anderson et al. (2012) found that exposure to 4-oxopentanal causes increased allergic and irritancy responses, both dermal and pulmonary. 4-Oxopentanal is a dicarbonyl that is a common reaction product between ozone and squalene, a component of human skin oil (Wisthaler and Weschler, 2010).

While researchers have in recent years increased the knowledge base related to ozone reaction products in buildings, the toxicological and epidemiological data related to nearly all of those products is insufficient to quantify health effects in humans. However, in a comprehensive review of the indoor air and health literature, Logue et al. (2011) predicted that exposure to formaldehyde and acetaldehyde are important health hazards in residential buildings. The remainder of this section focuses on these two pollutants, each of which has a contribution associated with indoor ozone chemistry.

Formaldehyde is ubiquitous in both residential and non-residential buildings. Nearly 70% of formaldehyde exposure occurs indoors (Loh et al., 2007). Pressed wood products such as particleboard and medium density fiberboard are major indoor sources. But formaldehyde is also an important product associated with ozone reactions with some unsaturated organic compounds found in indoor air and on materials (Singer et al., 2006; Weschler, 2006; Weschler and Shields, 1996).

Formaldehyde is classified as a hazardous air pollutant (HAP) under the Clean Air Act. It is widespread in residential and commercial buildings and is an acute eye and upper respiratory tract irritant. The California chronic Reference Exposure Level (REL) for formaldehyde is 9 μg/m^3, and is based on positive associations, especially among children with diagnosed asthma, between prolonged exposures to formaldehyde and allergic sensitization, respiratory symptoms (e.g. coughing, wheezing), or decrements in lung function (OEHHA, 2008). Several researchers have observed median formaldehyde concentrations in U.S. homes representative of the larger housing stock that are between 1.9 and 2.4 times greater than the California REL (Gordon et al., 1999; Sax et al., 2006; Weisel et al., 2005). Logue et al. (2012) predicted that formaldehyde accounted for the second highest contribution to DALYs behind acrolein amongst hazardous air pollutants found in U.S. homes.

There is some disagreement as to the importance of formaldehyde on non-cancer effects at typical indoor concentrations. Wolkoff and Nielsen (2010) provided a detailed review of non-cancer effects of formaldehyde. They concluded that there is no experimental or epidemiological evidence amongst either children or adults that indicate lung effects for formaldehyde exposures less than 1 mg/m^3 (≈ 800 ppb at typical indoor temperatures). Others have noted that there is inconsistent evidence that formaldehyde causes asthma or other chronic respiratory diseases (Checkoway et al., 2012, and references provided therein).

Formaldehyde is classified as a probable human carcinogen (Group B1) by the U.S. Environmental Protection Agency and carcinogenic to humans (Group 1) by the International Agency for Research on Cancer (IARC). Tests on rats and mice have shown an increase in nasal squamous cell carcinomas due to long-term exposure to formaldehyde (USEPA, 2014c). Zhang et al. (2010) found that increased formaldehyde exposure (2.14 ppm vs. 0.026 ppm for control) in factory workers led to decreased white blood cell production; white blood cell counts for workers exposed to higher formaldehyde concentrations were 13% less than the counts for the control group. They also observed that some exposed workers experienced the loss of chromosome 7 in molecular DNA, which is a preliminary indicator of cancer. Myeloid leukemia has been shown to have a higher incidence among professions commonly exposed to formaldehyde and formalin-based fixatives such as anatomists, embalmers, and garment workers (Zhang et al. 2010). Several authors have noted the potentially high contribution of formaldehyde to cumulative cancer risk from exposure to air contaminants that are typically found in residences (Hun et al., 2010; Loh et al., 2007; Sax et al., 2006).

However, the carcinogenic effects of formaldehyde also remain a topic of debate. Arts et al. (2006) point out that formaldehyde is not carcinogenic in rats at a sustained exposure of less than 6 ppm. Checkoway et al. (2012) concluded that there is currently no consistent or strong epidemiologic evidence that formaldehyde is causally related to any lymphohematopoietic malignancies. Further, Wolkoff and Nielsen (2010) conclude that at concentrations less than 100 ppb formaldehyde will not lead to cancer risks in the general population.

Amongst other sources, acetaldehyde is formed via reactions between ozone and unsaturated organic compounds (Lee et al., 2006a and 2006b). It is classified as a probable human carcinogen (Group B2) by the USEPA (2012). Increased tumor formation in rats and chromosomal damage to mammal cellular cultures (USEPA, 2014c) have been attributed to elevated exposures to acetaldehyde. It is a common pollutant associated with environmental tobacco smoke (Nazaroff and Singer, 2004) and approximately 15% of acetaldehyde exposure occurs in indoor environments (Loh et al., 2007). Loh et al. (2007) also found that acetaldehyde has the sixth highest cancer risk among common HAPs found indoors. Logue et al. (2012) predicted that indoor acetaldehyde exposure is responsible for the fourth highest DALYs among gaseous indoor air pollutants, behind only acrolein, formaldehyde, and ozone.

There are a large number of additional reaction products that form as a result of indoor ozone chemistry. Carbonyls formed as a result of indoor ozone chemistry are irritants; heavier carbonyls tend to have lower irritation thresholds (Cometto-Muñiz and Abraham, 1998). Suspect irritants include pinonaldehyde, a stable di-aldehyde that is formed at high yield in the ozone/α-pinene reaction. Anderson et al. (2007 and 2010) found, through the application of quantitative structure activity relationships, animal models and in-vitro exposure systems, that most dicarbonyl compounds are irritants and sensitizers. Organic acids tend to be roughly 10 times as irritating as their analogous aldehydes; a number of acids (e.g., formic acid), di-acids (e.g., pinic acid) and acid/aldehyde compounds (e.g., norpinonic acid) are also formed from indoor ozone chemistry. Intermediate products, such as ozonides, and hydroperoxy radicals are highly reactive and may also interact strongly with mucous membranes. Several researchers have noted that products of reactions between ozone and terpenes are strong airway irritants (Wolkoff et al., 1999 and 2000; Weschler et al., 2006, and references presented therein). As evidence of eye irritation, the limonene–ozone reaction mixture caused eye-blink frequency to increase in human subjects (Klenø and Wolkoff, 2004). These findings are important and worthy of continued attention. However, we were unable to find data or supporting models that will allow determination of quantifiable health impacts, e.g., mortality or DALYs, from such products on human populations.

2.2.3. Health Effects of Secondary Organic Aerosols

Secondary organic aerosols are a well-documented and major reaction product associated with indoor ozone chemistry. However, sparse toxicological and epidemiological data preclude explicit estimates of the health effects of human exposure SOA formed indoors.

Wolkoff et al. (2008) used a mouse bioassay and indicated significant sensory effects upon exposure to mixtures of d-limonene and ozone. However, gas-denuded results showed no effect, leading the authors to conclude that ultrafine particles formed from ozone/limonene chemistry are not causative of sensory effects in the airways.

Some fraction of outdoor $PM_{2.5}$ is SOA, and the quantifiable health effects of outdoor $PM_{2.5}$ might be extendable to indoor SOA, albeit with substantial caveats and uncertainty. Logue et al. (2012) found that in 80% of simulated indoor samples in their study, $PM_{2.5}$ contributed to the highest number of DALYs among indoor air pollutants.

Evidence of $PM_{2.5}$ as a cardiovascular and respiratory health hazard has been validated extensively in the literature. In a 26-year study with a cohort of 188,699 non-smokers, Turner et al. (2011) observed a 15-27% increased risk of lung cancer mortality for each 10 $\mu g/m^3$ increase in ambient $PM_{2.5}$ concentration. Pope et al. (2011) evaluated the dataset from the 1.2-million-member American Cancer Society cohort and found that a 10 $\mu g/m^3$ increase in ambient $PM_{2.5}$ concentration led to an adjusted relative risk of 1.14 for lung cancer, 1.18 for ischemic heart disease, 1.12 for cardiovascular disease, and 1.09 for cardiopulmonary disease. They also determined that the $PM_{2.5}$ exposure-response curve is nearly linear for lung cancer and non-linear (response becomes asymptotic with higher exposure) for cardiovascular disease (Pope et al., 2011). Jerrett et al. (2009) observed that $PM_{2.5}$ exposure and related impacts was dominant in the two-pollutant model (ozone and $PM_{2.5}$) when compared to cardiopulmonary, cardiovascular, and ischemic heart disease related mortality, i.e., ozone had far less impact.

Finally, it is important to note that a large fraction of indoor SOA exists initially as ultrafine particles. Epidemiological studies on ultrafine particle exposure are not as extensive as $PM_{2.5}$. However, ultrafine particles can be transported through the blood stream and into vital organs such as the liver and brain, and have been noted to cause inflammatory responses in the respiratory system (Oberdorster et al., 2010). Hoek et al. (2010) developed mortality relative risk estimates for ultrafine particles and published the only paper found in the literature to predict a health outcome from ultrafine particles.

2.3. Ozone Removal by Activated Carbon

Activated carbon is formed by dehydration and slow heating of organic materials (e.g., coal, wood, coconut shells) in an anaerobic environment. The finished product has a large surface area to mass ratio (up to 1,000 m^2 per 1 g), which allows gaseous pollutants to adsorb to and/or react with sites on the AcC. Ozone is removed by chemisorption via two possible pathways: (1) reaction within a solid carbon matrix with C=C bonds to form epoxides, and (2) reactions with C=C bonds to form ozonides (Dusenbury & Cannon, 1996). At ambient ozone concentrations these reactions lead to the production of small amounts of carbon monoxide, carbon dioxide, water, and some surface functional groups (Dusenbury and Cannon, 1996).

Over time, the effectiveness of ozone removal by activated carbon is reduced due to consumption of reaction sites by ozone, physical decomposition of AcC by reactions with ozone, and the formation of acidic surface oxidation complexes (Álvarez et al., 2008; Lee and Davidson, 1999; Muller and Jin, 2009). Figure 2 shows scanning electron microscope images of activated carbon used in residential activated carbon filters exposed to low and higher concentrations of ozone for 2 hours. The images clearly show pitting and overall morphological changes of the activated carbon at elevated exposure to ozone.

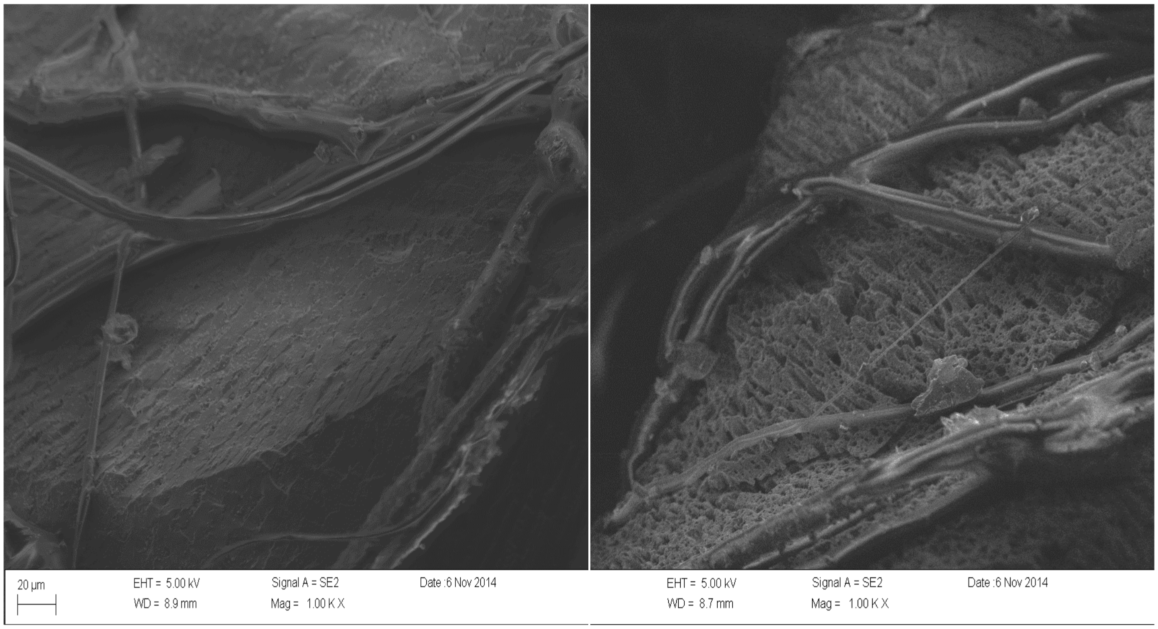

Figure 2. Scanning electron microscope (SEM) images of activated carbon filter material exposed to low ozone (L) and high ozone (R) for two hours. The SEM images were captured by the author of this dissertation at the University of Texas during operational testing of the carbon filters.

Experimental studies have indicated average capacities of 0.20-0.34 grams of ozone per gram of activated carbon at 50% ozone removal efficiency for beds of granular activated carbon and non-woven pleat filters loaded with activated carbon (Gundel et al., 2002; Shields et al., 1999; and references provided therein). As such, periodic replacement of activated carbon filters in order to maintain a design range of ozone removal efficiencies is required.

The presence of elevated relative humidity (RH) can reduce the ozone removal efficiency of AcC, presumably by blockage of reaction sites by water molecules (Álvarez et al., 2008). Others have tested volatile organic compound (VOC) loaded activated carbon filters and showed reduced ozone removal capacity depending on the type of adsorbed VOC and the extent of the loading (Metts and Batterman, 2006). On-filter heterogeneous reactions with d-limonene and resulting reaction products have also been observed (Metts, 2007). However, the VOC loadings in these studies were much higher than typically observed in most office buildings or homes.

Several research teams have explored the enhancement of activated carbon for improved removal of ozone and VOCs (Heisig et al., 1997; Kelly and Kincaid, 1993; Lin et al., 2008; Takeuchi and Itoh, 1993). Such enhancements have generally involved the introduction of metal catalysts such as gold or manganese by impregnation into or vapour deposition onto activated carbon. For example, Lin et al. (2008) showed that activated carbon fibers amended with gold or manganese by vapour deposition can significantly enhance ozone removal efficiency relative to activated carbon fibers that were not amended. However, experiments were completed at ozone concentrations 3 to 4 orders of magnitude higher than those typical of ambient air.

Lee and Davidson (1999) completed testing on ten different commercially available AcC filters used to remove ozone. Each filter was tested at an inlet ozone concentration of 120 ppb at 50% relative humidity. However, tests were completed for only several hours. In addition to testing for ozone removal, each filter was also evaluated for pressure drop at a face velocity of 2.54 m/s. Test air was pre-filtered with high efficiency particulate air (HEPA) filters, thus precluding particle deposition on the activated carbon filters. Results are summarized in Table 1. The ozone removal efficiency for most filters was initially high (> 94%) and then decreased slightly within the first thirty minutes of operation. The authors reported that there was no regeneration of the filters after removing them from ozone for up to 12 hours. The activated carbon fiber filter (filter #9 in Table 2.3.1) exhibited high ozone removal efficiency (98.3%) initially, but efficiency quickly decreased to less than 30% after 200 minutes of continuous exposure to ozone. Lee and Davidson (1999) theorized that this was caused by degradation of the micropore structure of the filter following oxidation by ozone. The activated carbon fiber filter also performed poorly with increases in relative humidity, likely due to water molecules blocking reaction sites on the surface of the activated carbon within the filter as described by others (Álvarez et al., 2008; Shields et al., 1999). Interestingly, the other activated carbon filters showed no changes in performance when RH was varied between 20% and 80%.

Shair (1981) appears to have been the first to complete field-testing of ozone removal using activated carbon. A make-up air filtration system was installed on a building in Pasadena, California, using an activated carbon filter bank consisting of nine 61 cm x 61 cm x 76 cm (24" x 24" x 30") AcC filters. A particle pre-filter that roughly corresponded to a contemporary MERV 7 filter was used. Ozone control was only used when outdoor concentrations of ozone exceeded 80 parts per billion (ppb). Testing was completed for three years, during which time the make-up air filtration unit ran approximately 1,200 hours per year at an average flow rate of 6.6 m^3/s (14,000 ft^3/min). After 1,200 hours of operation the AcC filters removed 95% (+/- 5%) of outdoor ozone and the efficiency slowly declined to 80% at 2,400 hours of operation. Ozone removal efficiency declined to 50% at 3,600 hours of operation. Pressure drop across the entire assembly (pre-filter, carbon filter, air monitor, diffuser, dampener, and final diffuser) was 0.29 kPa, which was accommodated by a 3.7 kW (5 hp) fan motor installed in the HVAC system.

Table 1. Summary of test results from Lee and Davidson (1999).

	Test Filter	**ΔP (kPa)**	**AcC Area/Mass (m^2 / g)**	**O_3 removal (%) (t = 0 - 30 min)**
1	3M Model E -- GAC Mesh (w/adhesive)	0.340 +/- 0.010	1,225	94.7 - 94.1%
2	3M Model R -- GAC Mesh	0.580 +/- 0.010	1,225	97.5 - 96.0%
3	Farr Company Farr Sorb PS -- Carbon spheres in foam	0.129 +/- 0.001	5,000	69.7 - 53.0%
4	AAF International Carbon Web -- GAC Mesh (w/adhesive)	0.151 +/- 0.001	1,226	52.1 - 38.0%
5	Hoechst Celanese AQF-2750 -- GAC Mesh in pleated sheets	1.070 +/- 0.010	*	97.3 - 94.7%
6	Hoechst Celanese CPS-9C500C -- GAC Mesh (pleated sheets)	3.700 +/- 0.010	*	98.0 - 93.9%
7	Columbus Industries Polysorb IO5200 -- impregnated carbon	0.165 +/- 0.001	*	94.7 - 94.1%
8	Columbus Industries SupraSorb -- impregnated carbon	0.053 +/- 0.001	*	94.7 - 94.1%
9	PICA USA ACTITEX FC-1200 Activated Carbon Fiber Filter	2.200 +/- 0.100	1,200	94.7 - 94.1%
10	Carus Chemical Company Carulite Ozone Catalyst	0.630 +/- 0.010	*	94.7 – 94.1%

All filters were 1.328 cm in diameter by 1.27 cm thick; tested at 120 ppb O_3, 50% RH, 2.54 m/s face velocity

* = not available (hybrid)

Shields et al. (1999) demonstrated that relatively large beds packed with granular activated carbon (GAC) (20 to > 200 kg) can efficiently remove ozone in an actual field test conducted between five to eight years of continuous service. Filters were tested in three different configurations over a period of eight years in two cleanrooms and a test plenum (Table 2). Inlet ozone concentrations ranged from 10 to 80 ppb. The test plenum had two pre-filters with an average flow rate of 0.28 m^3/s (600 ft^3/min). The AcC filter in the test plenum had a single-pass ozone removal efficiency of 90% after five years of continuous service. The first test classroom had a 30% (~MERV 5) pre-filter, followed by the AcC filter, and then an 85% (~MERV 10) post-filter in series with a flow rate of 10.2 m^3/s (21,700 ft^3/min). The charcoal filter in the first test classroom had an ozone removal efficiency of 60% after eight years of continuous service. The configuration of the second test classroom included 30% and 85% pre-filters upstream of cooling coils, followed by the AcC filter. The air flow rate through the system was 1.4 m^3/s (3,000 ft^3/min). The ozone removal efficiency was 70% after seven years of continuous service. Pressure drop across the filter assemblies was not provided by the authors. Shields et al. (1999) hypothesized that the lower ozone removal efficiencies in classroom #1 of their study were due to the lack of a pre-filter, especially since classroom #1 received 100% outdoor air. The absence of a pre-filter likely led to particle deposition onto GAC surfaces, thus shielding reaction sites from ozone. Furthermore, the lower air flow rate per mass of AcC through the filter in classroom #2 (20% lower than classroom #1) permitted a higher residence time for ozone in the filter and thus more time for ozone to react with filter surfaces.

Table 2. Field test results for ozone removal efficiencies from Shields et al. (1999).

	Flow rate (m^3 / s)	Mass AcC (kg)	Flow / Mass of AcC (m^3 / s*kg)	Filter Configuration primary + secondary + tertiary	Ozone Removal Efficiencies (%) 0.0 yrs	3.1 yrs	5.0 yrs
Test Plenum	0.28	20.41	0.01	MERV 5 + MERV 10 + AcC	95	90	90
Cleanroom #1	10.20	217.73	0.05	MERV 5 + AcC + MERV 10	85	60	60
Cleanroom #2	1.41	40.82	0.03	MERV 5 + MERV 10 + AcC	95	95	92

*All units in the table above were originally presented in English units and have been converted to metric units

Combination filters incorporating activated carbon have also been investigated for ozone removal. Bekö et al. (2009) tested four types of filters for ozone removal over six months of continuous field-testing (Table 3). The tests included three combination filters (F7 + carbon) with varying amounts of carbon (light, medium, and heavy) evaluated at field conditions versus a baseline condition (F7 filter with no carbon). Results clearly demonstrate increases in pressure drop (ΔP) and ozone removal efficiency with increasing activated carbon density.

Table 3. Summary of test results from Bekö et al. (2009).

Filter	ΔP (kPa) 0 mos.	ΔP (kPa) 3 mos.	ΔP (kPa) 6 mos.	O_3 Removal (%) 6 mos. Average
F7 (MERV 13) Fiberglass (No Carbon)	0.074 +/- 0.001	0.077 +/- 0.001	0.078 +/- 0.001	10%
F7 (MERV 13) + Light Carbon (100 g/m^2)	0.089 +/- 0.001	0.088 +/- 0.001	0.095 +/- 0.001	17%
F7 (MERV 13) + Medium Carbon (200 g/m^2)	0.103 +/- 0.001	0.095 +/- 0.001	0.102 +/- 0.001	28%
F7 (MERV 13) + Heavy Carbon (400 g/m^2)	0.130 +/- 0.004	0.132 +/- 0.001	0.144 +/- 0.001	59%

All tested filter dimensions were 0.6m x 0.6m x 0.3m deep; tested at 21°C, 35% RH, 2.0 m/s face velocity.

Bekö et al. (2008) also tested several configurations of combination filters under field conditions (varying temperature, relative humidity, and ozone concentration) over a five-month test period. Although ozone removal efficiencies were not reported, pressure drop data related to various filter configurations were measured. Data are summarized in Table 4.

Table 4. Summary of test results from Bekö et al. (2008).

First Filter	ΔP (kPa) 0 mos. 5 mos.	Second Filter	ΔP (kPa) 0 mos. 5 mos.	Third Filter	ΔP (kPa) 0 mos. 5 mos.
85% Filter (EU7/F7/ MERV 13 Equivalent)	0.052 +/- 0.001 0.065 +/- 0.004	V-Cell Cartridge (1.7 kg AcC)	0.049 +/- 0.001 0.057 +/- 0.001	None	--- ---
AcC V-Cell Cartridge (1.7 kg AcC)	0.052 +/- 0.001 0.052 +/- 0.002	85% Bag Filter (EU7/F7/ MERV 13 Equivalent)	0.075 +/- 0.001 0.086 +/- 0.001	V-Cell Cartridge (1.7 kg AcC)	0.048 +/- 0.001 0.050 +/- 0.001
EU7/F7/MERV 13 Combo Bag Filter (1.3 kg AcC)	0.110 +/- 0.003 0.102 +/- 0.003	None	--- ---	None	--- ---
EU7/F7/MERV 13 Combo Cartridge Filter (1.3 kg AcC)	0.123 +/- 0.002 0.151 +/- 0.004	None	--- ---	None	--- ---

All filters tested at 1,300 m^3/hr flow rate, 2.0 m/s face velocity.

Fisk et al. (2009) studied the performance of MERV 8 hybrid (combination) filters placed in an office building in Sacramento, California, for an 81-day period from late summer to mid fall. Each filter had dimensions of 61 cm x 61 cm x 5.1 cm (24" x 24" x 2"), contained 300 g of AcC per 0.09 m^2 of filter face, and cost $29/filter. The filters were used as pre-filters in two filter banks of the building. A third filter bank that included a similar pre-filter without activated carbon was also studied for comparison. For most of the 81-day test period the filters were challenged with primarily re-circulated air with low concentrations of ozone that made it difficult to accurately quantify ozone removal efficiencies. Toward the end of the study analyses were completed with 100%

outdoor air supply. During this two-week period the filters containing AcC removed 60% and 70% of ozone. Importantly, the filter that did not contain AcC removed no ozone. It is not clear whether ozone removal efficiency would have been lower had the AcC filters been challenged with a greater fraction of outdoor air throughout most of the test period. However, the results presented by Fisk et al. (2009) are encouraging given that they represent an actual application for a nearly three month operating period in an office building with relatively low-cost AcC filters.

Muller and Jin (2009) tested a combination filter under field conditions over a three-month period in Atlanta, Georgia. A MERV 6 filter in a commercial building was replaced with a 10-cm (4-in) thick combination filter with embedded activated carbon. The filter was evaluated for ozone and VOC removal over the test period and demonstrated a continuous ozone removal efficiency of greater than 90% during peak ozone season in Atlanta (May-September). The average ozone concentration over the test period was 39 ppb with a peak concentration of 145 ppb. Information on temperature, relative humidity and pressure drop during the field-testing program was not provided.

The life cycle costs of in-duct AcC filtration have not been extensively documented in the published literature. Shair (1981) described the capital and operating costs of retrofitting an existing HVAC system with AcC filters to remove ozone. The capital costs for installing a system in a commercial-type building was $12,000 in 1975, with an annualized maintenance and operation cost of $600 per year.

More recently, Stanley et al. (2011) completed a life-cycle valuation of several AcC filters used for ozone removal in a hypothetical hospital air handler with an air flow rate of 3,398 m^3/hr (2,000 ft^3/min). Their analysis included the following filter types: carbon-loaded non-woven pleat, cassette with internal V-bank, granular activated carbon in honeycomb tray, granular activated carbon in V-bank formation, and adsorbent extruded into an open honeycomb matrix. A MERV 8 pre-filter and MERV 14 final filter was assumed. Cost analyses were completed based on filter replacement (including labor costs), energy consumption, and additional hardware requirements. Annualized costs were determined as increases above a base cost without AcC filtration. After removing one outlier, the range of annualized incremental cost increases across seven filter systems was \$0.05-\$0.16/(m^3/hr). This range translates to \$170 to \$540 for a hospital air handler that moves 3,398 m^3/hr (2,000 cfm). Importantly, Stanley et al. (2011) assumed continuous (24 hours a day, 365 days per year) operation of the air handling system. This assumption likely overestimates annual operating costs, as energy costs due to pressure drop accounted for nearly 50% of the annual operating costs in their assessment.

3. POPULATION MODEL DEVELOPMENT

3.1. Model Derivation

The model developed for this project consists of an integrated system of mathematical equations that address several major model components and their interconnections. A detailed description of the model is provided in Appendix A. The model is intended for determining indoor concentrations of ozone and ozone reaction products in multiple types of buildings, and potential benefits and costs associated with commercially available ozone air-cleaning devices (OACD) in HVAC systems. Major model components and their connections are shown in Figure 3.

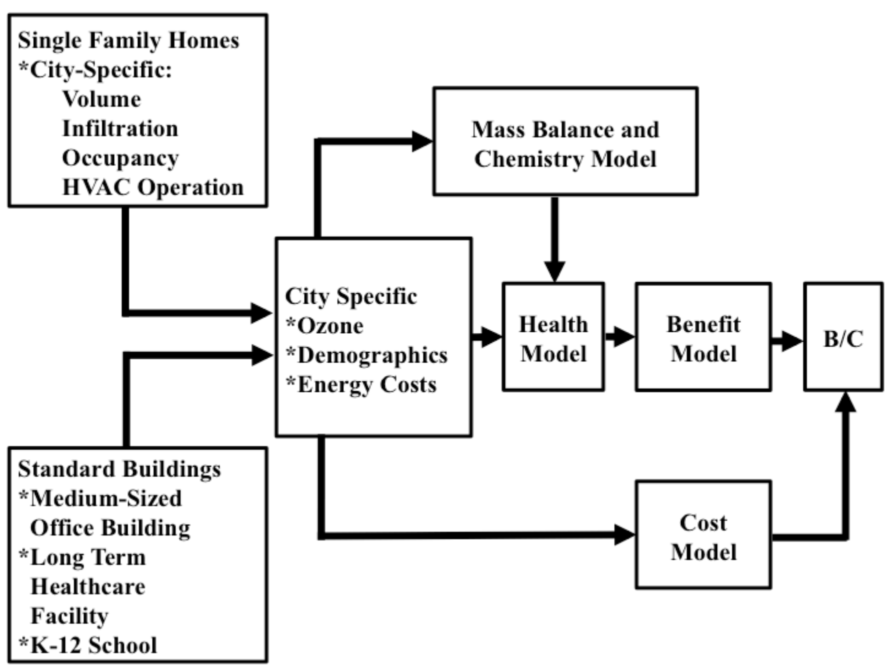

Figure 3. Illustration showing the interconnected sub models of systems model.

Modeling the Effects of Climate, Geography, and Demographics

The modeling analysis focused on a set of baseline conditions in 12 cities across the United States – the conditions are discussed in further detail in Appendix A. At least two cities from each of the five climate zones defined by the Energy Information Administration were selected for the analysis (USEIA, 2014). Climate zones are defined by number of heating degree-days and cooling degree-days. The cities selected for this analysis include: Atlanta, Austin, Buffalo, Chicago, Cincinnati, Houston, Miami, Minneapolis, New York City, Phoenix, Riverside, and Washington D.C. (Figure 4). This sample of cities accounts for a broad nationwide sample of population, climate, building stock, and ambient ozone concentrations.

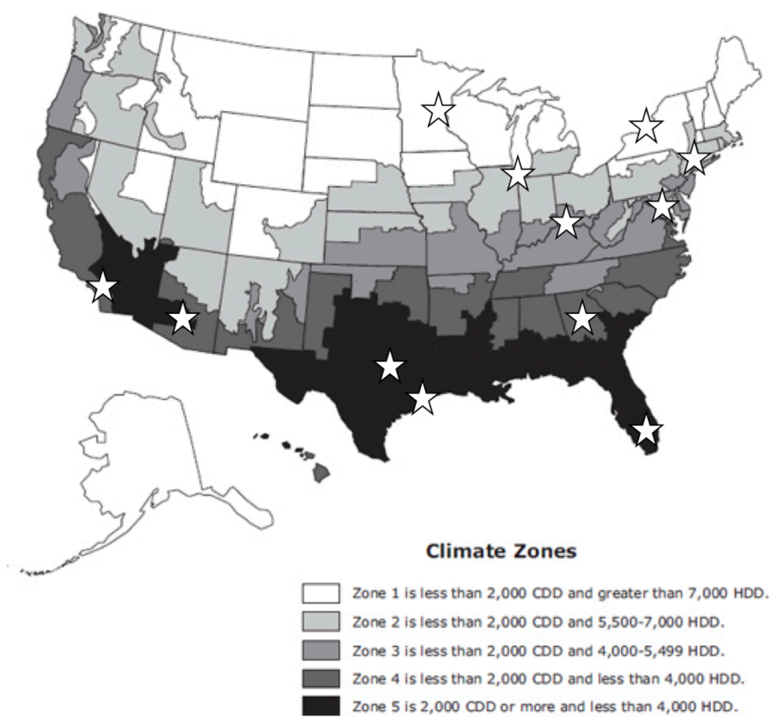

Figure 4. U.S. climate zones and geographic location of 12 sample cities (USEIA, 2014).

In addition, city-specific parameters such as the average occupancy of single-family homes, population age fractions, and regional energy costs were also accounted for in the integrated systems model. Single-family homes were modeled using a Monte Carlo analysis and city-specific housing parameters to determine the ozone removal effectiveness and benefit/cost (B/C) ratio of activated carbon filtration. Details of the Monte Carlo analysis methodology and results for single-family homes are described in Appendix A.

Commercial buildings, including office buildings, long term healthcare facilities, and K-12 schools were modeled using standardized building parameters defined by (list who standardizes these and provide references) and city-specific ozone, demographics, and energy costs. Details on the methods and results of the commercial building modeling analysis are provided in detail in Appendix B. In all buildings, the major parameters influencing the benefit-to-cost ratio include outdoor ozone, the make-up ventilation rate, HVAC operation fraction, cost per kWh of electricity, and filter efficiency (i.e., single-pass removal efficiency for ozone) of the activated carbon filter.

Mass Balance and Chemistry Model

Core model equations are used to solve for ozone concentration and concentrations of key reaction products as previously presented by Fadeyi (2014), Chen et al. (2012a), and Weschler and Shields (2000). The model is designed to estimate concentrations of ozone and reaction product concentrations for scenarios without any control devices and scenarios with control devices in place. The differences in these scenarios are used to quantify the health benefits of ozone control. The fate of ozone and ozone reaction products within a building or zone are estimated using mass balance equations based on assumptions of well-mixed and steady-state conditions. The time-averaged mass balance equations for ozone and ozone reaction products are presented as Equations (1) and (2), respectively.

$$C_{O3} = \frac{\{p\lambda_{inf}+(1-f_{f,O3})(1-f_{c,O3})H_{on}\lambda_{make-up}\}C_{o,O3}+{}^{E_{O3}}/_{V}}{\lambda_{exh}+H_{on}\lambda_{rec}\{1-(1-f_{f,O3})(1-f_{c,O3})\}+k^{*}_{dep,O3}+\sum_j k_j C_j} \tag{1}$$

$$C_{pi} = \frac{y_{si}k^{*}_{dep,O3}C_{O3}+\sum_j y_{i,j}k_j\,C_j C_{O3}\alpha_j+{}^{E_{pi,f}}/_{V}}{\lambda_{exh}+H_{on}\lambda_{rec}\{1-(1-f_{f,pi})(1-f_{c,pi})\}+k^{*}_{dep,pi}} \tag{2}$$

Where,

λ_{inf}	=	Q_{inf}/V [hr^{-1}]
$\lambda_{make-up}$	=	$Q_{make-up}/V$ [hr^{-1}]
λ_{rec}	=	Q_{rec}/V [hr^{-1}]
λ_{exh}	=	Q_{exh}/V [hr^{-1}]
H_{on}	=	average annual fraction of time that the HVAC system operates [-]
C_{O3}	=	concentration of ozone in the occupied space [ppb]
$C_{o,O3}$	=	concentration of ozone in outdoor air [ppb]
C_j	=	concentration of gaseous reactant j in the occupied space [ppb]
E_{O3}	=	emission rate of ozone into occupied space [ppb • m^3 • hr^{-1}]
$E_{pi,f}$	=	emission rate of product i from HVAC filter [ppb-m^3/hr]
	=	$y_{f,pi}H_{on}f_{f,pi}(Q_{make-up}C_{o,o3} + Q_{rec}C_{o3})$
$f_{c,O3}$	=	single-pass fractional removal of ozone by OACD [-]
$f_{f,O3}$	=	single-pass fractional removal of ozone by HVAC filter [-]
k_j	=	bimolecular homogeneous reaction rate constant [ppb^{-1} • hr^{-1}]
$k^{*}_{dep,O3}$	=	ozone decay rate for integrated background surfaces [hr^{-1}]

$k^{*}_{dep,pi}$ = ozone reaction product decay rate for background surfaces [hr^{-1}]

p = fractional penetration through the building envelope for ozone [-]

Q_{exh} = exhaust air volumetric flow rate [$m^3 \bullet hr^{-1}$]

Q_{inf} = infiltration air volumetric flow rate [$m^3 \bullet hr^{-1}$]

$Q_{make\text{-}up}$ = make-up (outdoor intake) air volumetric flow rate [$m^3 \bullet hr^{-1}$]

Q_{rec} = recirculation air volumetric flow rate [$m^3 \bullet hr^{-1}$]

V = volume of occupied space [m^3]

α_j = conversion factor (ppb to $\mu g/m^3$) for reactant j (used only for SOA formation)

$y_{i,j}$ = molar (or mass for SOA) yield of product i from ozone reaction with j [($moles_i/moles_j$) for gas or ($\mu g_i/m^3$ / $\mu g_j/m^3$ for SOA]

y_{si} = molar (or mass for SOA) yield of product i from ozone reaction with background surfaces [($moles_i/moles_{O3}$) for gas or ($\mu g_i/m^3$ / $\mu g_{O3}/m^3$ for SOA]

$v_{d,O3}$ = deposition velocity of ozone to background surfaces [m/hr]

$v^{*}_{d,pi}$ = deposition velocity of reaction product i to background surfaces [m/hr]

Benefit Model

Benefits are calculated using reductions in disability-adjusted life-years (DALYs) due to reductions in indoor ozone concentration following the application of activated carbon filtration. Disability-adjusted life-years are a metric for quantifying the burden of disease, and incorporate years of life lost from premature mortality and years of life lost from disability due to the incidence of disease. The methodology for determining change in health incidence and the corresponding value of DALYs follows previous work completed by the USEPA (2012b, and references provided therein) and others (Logue et al., 2012; USEPA, 2010; Huijbregts et al., 2005). The health functions and parameters used in the health analysis for ozone are presented in Table 5. Health functions for acetaldehyde and formaldehyde are provided in Appendix A.

Table 5. Health outcomes due to ozone exposure.

Health Outcome	ICD-9 Code	*β* *(95% CIs)*	DALYs per Incidence	Sources
Mortality (25 to 34)	J00-J99	0.0045 (0.0015, 0.0074)	27.14	USEPA (2010); Jerrett et al. (2009); USEPA (2012b); Lopez et al. (2006)
Mortality (35 to 44)	J00-J99	0.0045 (0.0015, 0.0074)	24.78	
Mortality (45 to 54)	J00-J99	0.0045 (0.0015, 0.0074)	22.42	
Mortality (55 to 64)	J00-J99	0.0045 (0.0015, 0.0074)	18.58	
Mortality (65 to 74)	J00-J99	0.0045 (0.0015, 0.0074)	13.36	
Mortality (75 to 84)	J00-J99	0.0045 (0.0015, 0.0074)	9.64	
Mortality (85+)	J00-J99	0.0045 (0.0015, 0.0074)	5.45	
Respiratory HA (18 to 64)	460-519	0.0020 (0.0010, 0.0030)	0.03	USEPA (2012b); Logue et al. (2012); Burnett et al. (1999); Lvovsky et al. (2000)
Dysrhythmia HA (18 to 64)	427	0.0020 (0.0000, 0.0040)	0.03	
Dysrhythmia HA (65+)	493	0.0020 (0.0000, 0.0040)	0.03	
MRAD (18 to 64)		0.0026 (0.0011, 0.0041)	0.0005	Hubbell et al. (2005); Ostro and Rothschild (1989); USEPA (2012b)
School Loss Day (5 to 17)		0.0158 (0.0060, 0.0255)	0.0007	Hubbell et al. (2005); Chen et al. (2000); USEPA (2012b)
Respiratory HA (65+)	460-519	0.0021 (0.0013, 0.0029)	0.03	USEPA (2012b); Moolkavgar et al. (1997); Lvovsky et al. (2000)

ICD-9 = International Classification of Disease, version 9
HA = Hospital Admission
MRAD = Minor Restricted Activity Day

The change in disease incidence for each modeling scenario is calculated using a baseline condition (no ozone control) and then subtracting the disease incidence when ozone control is applied and lower occupant exposures to both ozone and its reaction products occur (Equation 3). The calculations include parameters for baseline incidence, concentration-response (C-R) functions, DALYs per incidence, and city-specific age populations (USEPA, 2012b; USEPA, 2011a; USEPA, 2011b; USEPA, 2011c; Logue et al., 2012, US Census Bureau, 2012). The value of y_0 is specific to the disease or health condition being considered and changes depending on the pollutant, health outcome, and age.

$$\Delta\ Incidence = [y_0 * (1 - e^{-(\beta \Delta C(freq))})] * population \qquad \textbf{(3)}$$

Where,

$\Delta Incidence$ = change in disease incidence for a population [number of disease outcomes]

y_0 = baseline prevalence of disease $\left[\frac{\text{Health Outcomes}}{\text{Population-Year}}\right]$

β = concentration-response coefficient $\left[\frac{\text{Relative Risk}}{\text{Concentration}}\right]$

ΔC = change in pollutant concentration [$\mu g \cdot m^{-3}$]

$freq$ = exposure frequency, or fraction of one year where exposure occurs [-]

The number of DALYs per pollution exposure is calculated using Equation (4), and the estimated health benefit is calculated using Equation (5).

$$\text{DALYs} = \left[\frac{\text{DALYs}}{\text{Incidence}}\right] * \Delta Incidence \qquad \textbf{(4)}$$

$$Benefits = \$/DALY \text{ x } \Delta DALYs \qquad \textbf{(5)}$$

Where,

Benefit = monetary benefit associated with reduced DALYs per 100,000 people [$]

$/DALY = value of one disability adjusted life year [$$\cdot$year^{-1}]

Δ*DALYs* = reduction in DALYs (relative to no control) when a control is used [years]

When calculating DALYs, the number of years of life lost per mortality is dependent on the age at which mortality occurs (Lopez et al., 2006). The greatest uncertainty in the benefits analysis is attributed to the value of an avoided DALY, more specifically, what the average person is willing to pay to avoid a health-related issue due to ozone exposure. One generally accepted approach is to equate one DALY avoided as approximately equal to three times the per capita gross domestic product (Rascati, 2006). In the United States, this is equivalent to approximately $150,000 (2014 US dollars) per avoided DALY (World Bank, 2014). Bobinac et al. (2014) also evaluated the value of a quality-adjusted life-year (QALY) gained in the Netherlands using a survey incorporating a broad range of ages, incomes, and educational levels. One QALY gained is equivalent to one avoided DALY. Their methods used a weighting factor from Tversky and Kahneman (1992) to integrate decision theory and human behavior under risk. From their survey results, they were able to estimate a probabilistic distribution of what the average person is willing to pay to gain a QALY. Their results indicated a distribution with a mean of approximately \$140,000 (2014 US dollars) per avoided QALY.

For this dissertation, a distribution of dollars per avoided DALY was developed based on Bobinac et al. (2014), and was used to estimate the benefits of reduced exposure to ozone and its reaction products. This method yields lower benefits than the USEPA methodology used in the Regulatory Impact Analysis for ozone (USEPA, 2008). The USEPA uses a value per statistical life (VSL) of approximately \$9.3M (2014 U.S. dollars) per life lost regardless of age at the time of death (USBLS, 2014; USEPA, 2011b). In contrast, the DALYs method assigns a value of life based on the years of life lost compared to the average life expectancy, which results in lower benefits when compared to the USEPA method. Further information on the DALYs calculations and benefit model are provided in the supplemental information.

Cost Model

Overall filter costs include the difference in capital costs (materials and labor) between a standard particle filter and an activated carbon filter, as well as additional energy costs due to the difference in pressure drop between a standard particle filter and an activated carbon filter. Other costs such as installation and disposal are not included in this paper as our analysis focused on commercially available filters designed for residential HVAC systems. Overall filter costs are calculated for a population of 100,000 using Equation (6) and assuming one to two filters per residential HVAC unit during the summer ozone season (1 May through 30 September):

$$Costs = \left[[P_{elec} * E_{cost}] + [(F_{cost} + L_{cost}) * (RF)] \right] * \left[\frac{100{,}000}{Occ.} \right] \quad \textbf{(6)}$$

Where,

$Costs$ = overall differential cost between activated carbon and conventional particle filters (AcC – particle) per 100,000 persons [$]

P_{elec} = electricity usage [kWh] due to additional pressure drop = $= \left[\frac{Q_{filter} * \Delta P_{diff} * H_{on\_tot}}{1000 * \eta_{HVAC}} \right]$

E_{cost} = electricity cost per kWh [$]

Q_{filter} = flowrate through the filter [$m^3 \cdot hr^{-1}$]

ΔP_{diff} = difference in pressure drop across the filter between AcC filter and standard filter [Pa]

H_{on_tot} = total number of hours of HVAC operation [hours]

η_{HVAC} = overall efficiency of the HVAC fan and motor [-]

F_{cost} = difference in filter costs between AcC filter and standard particle filter [$] (assumed to equal zero for residences)

L_{cost} = difference in labor, replacement, and disposal costs between AcC and particle filters [$] (assumed to equal zero for residences)

RF = filter replacement frequency [yr^{-1}]

$Occ.$ = building occupancy [persons] (average varies by city)

City specific electricity costs and HVAC operational runtimes are provided in greater detail in the Appendix A. Overall filter costs are extrapolated for a population of 100,000 in order to compare with DALYs using the same metric (per 100,000 people).

3.2. Model Results

Proprietary ozone removal efficiency data provided by a filter manufacturer estimated an ozone removal efficiency ranging from 60-90% during an 8-week field test in a hot and humid climate. In order to provide conservative estimates of the filter performance in single-family homes (typically 1-inch filters), an ozone removal efficiency of 40% was used in the modelling analysis. The modelling results indicate that an activated carbon filter with an ozone removal efficiency of 40% would provide marginal benefits in single-family homes (Figure 5). Further information on the methodology and modelling results are presented in Appendix A and Appendix B.

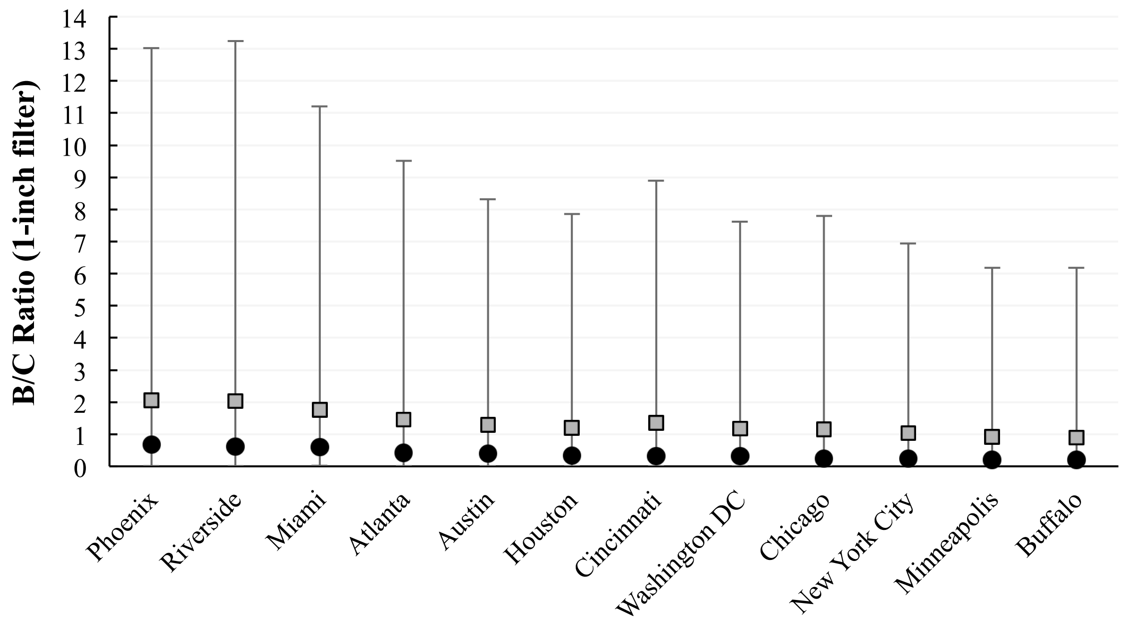

Figure 5. Benefit-to-cost ratios from using 1-inch (2.5 cm) activated carbon filters in single-family homes. The filled circles represent median values, the filled boxes represent means, and the whiskers represent the 95% confidence intervals of the Monte Carlo modeling analysis.

Of the 12 target cities, single-family homes in Phoenix would benefit the most from carbon filtration, followed closely by Riverside. For each of these two cities the mean B/C ratio is approximately 2.0. High summertime ozone concentrations and relatively new building stocks characterize these two cities with high air conditioning usage during summer months. This implies that cities with high summer temperatures (and by extension high air conditioning usage), high summertime ozone, and a high proportion of residential air conditioning usage (implying newer building stock) will benefit the most from residential carbon filtration. Cities that had lower B/C ratios include Buffalo and Minneapolis. These two cities are characterized by a milder summer climate and generally lower air conditioning usage (Chen et al., 2012a and 2012b). In addition, since both cities have milder climates and older building stock, residents may generally open windows for cooling, eliminating the benefit of activated carbon filters (Chen et al., 2012a). The upper bound of B/C ratios for each city ranged from approximately 6 to 13, indicating that some fraction of the population receives significant benefits from activated carbon filtration on residential buildings. This subset is generally characterized as a subpopulation with existing respiratory sensitivities (asthma, and other chronic pulmonary disorders), as well as the population over the age of 65, which generally has a much higher incidence rate for respiratory morbidity and mortality.

Since the results of activated carbon filtration in single-family homes in Phoenix appear promising, a secondary analysis of avoided mortalities was conducted. Berman et al. (2012) compared ozone-related mortalities in Phoenix over three years and three different ozone rollback strategies. The rollback strategies were in accordance with new 8-hour ozone standards proposed by the USEPA. These analyses in Berman et al. (2012) were then compared to the number of avoided mortalities in Phoenix when using activated carbon filters in single-family homes with air conditioning. As shown in Figure 6, utilizing activated carbon filtration in single-family homes would result in nearly equivalent numbers of avoided mortalities when compared to rolling back the 8-hour ozone standard to 70 ppb.

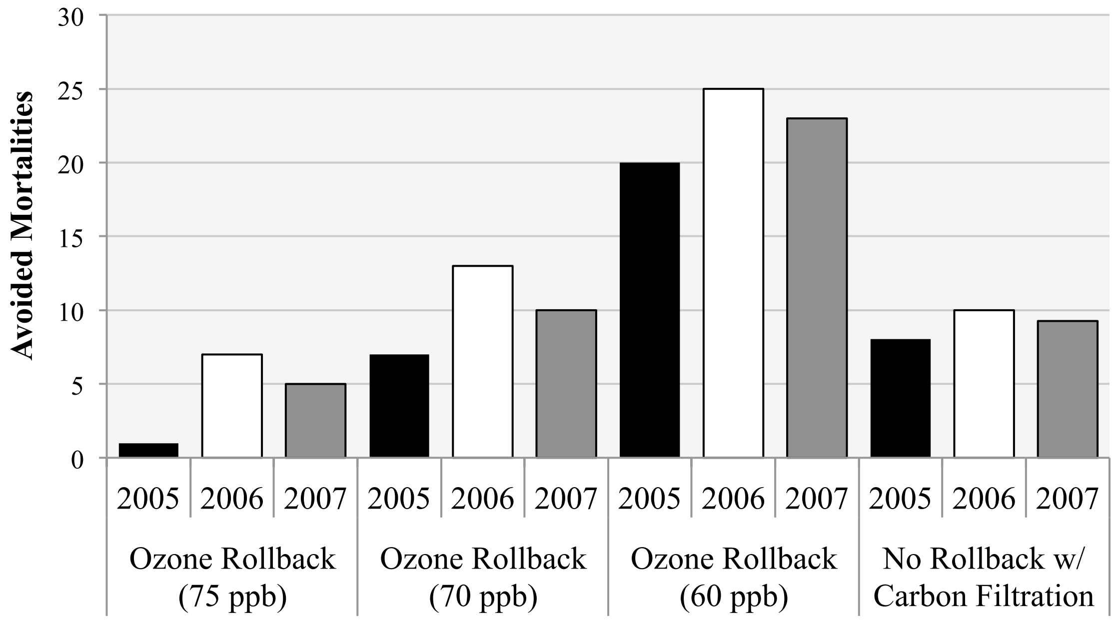

Figure 6. Comparison of avoided mortalities per year in Phoenix, AZ under three different 8-hour ozone rollback strategies and with activated carbon filtration in single-family homes.

When utilizing the USEPA's value of a statistical life of approximately $9.8M and comparing versus the control costs for each strategy (USEPA, 2011 and USEPA, 2008), the control costs for activated carbon filtration in single-family homes is nearly one order of magnitude less than the control costs for outdoor ozone reductions (Figure 7). When utilizing activated carbon filtration with 100% HVAC fan operation during the summer ozone season, the benefits of carbon filtration are greater than the costs. This implies that activated carbon filtration in homes could be cost-effective at reducing ozone-related mortalities and should be considered as a strategy to improve public health.

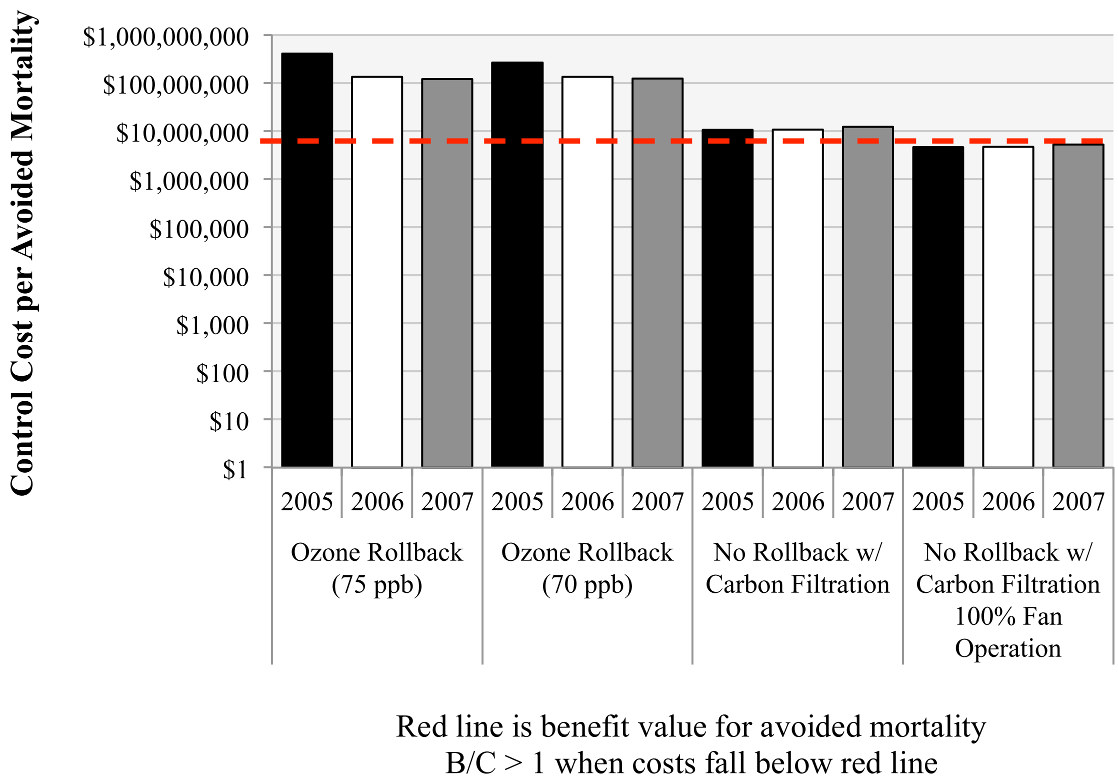

Figure 7. Comparison of annual ozone control costs per avoided mortality in Phoenix, AZ comparing two 8-hour ozone rollback strategies and two strategies utilizing activated carbon filtration in single-family homes.

For commercial buildings, the modelling results indicate that an activated carbon filter with an ozone removal efficiency of 60% would provide annual benefit-cost ratios equal to or greater than 1.0 in all three building types across all 12 cities as shown in Figure 8.

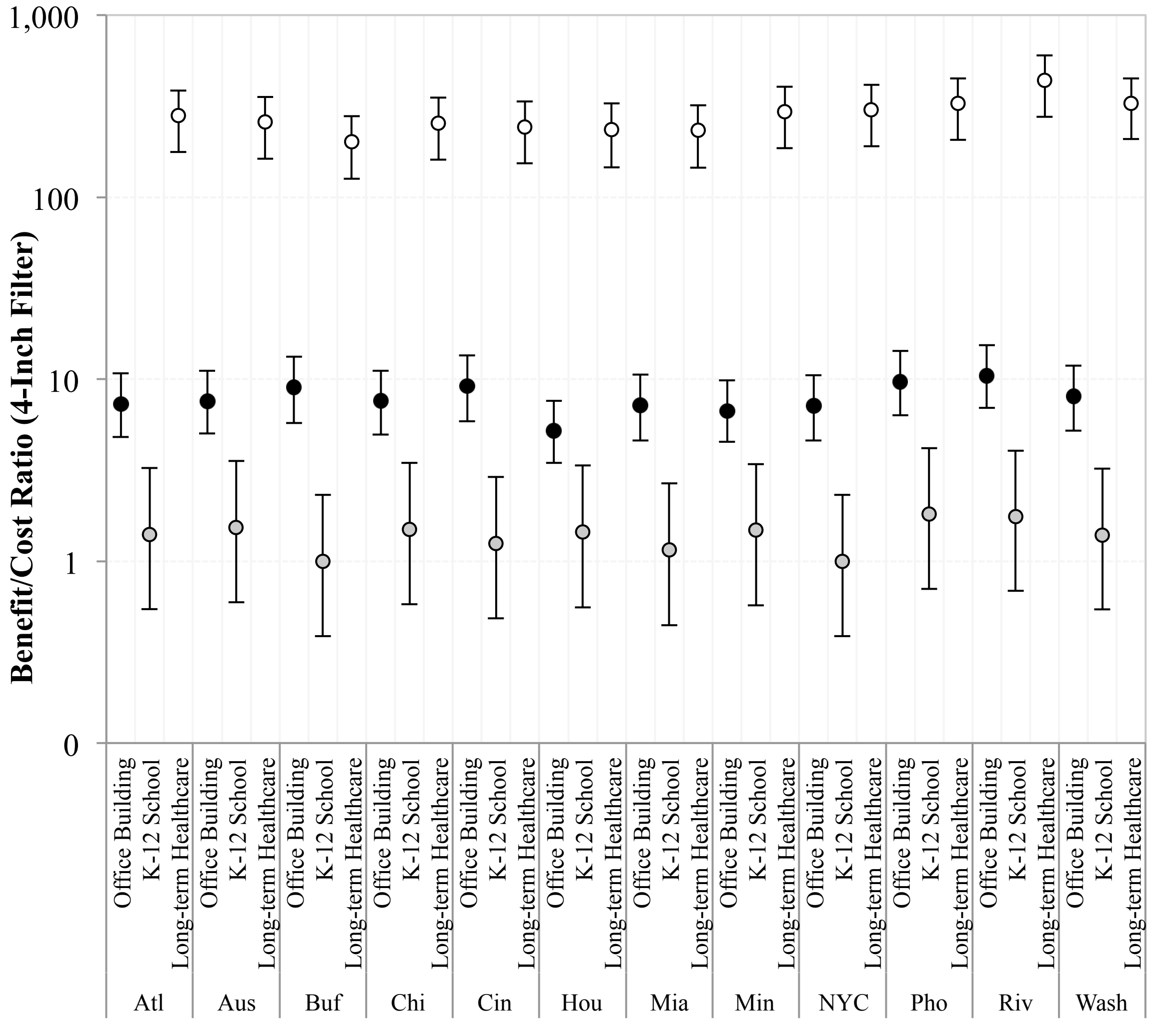

Figure 8. Predicted benefit/cost ratios in commercial buildings when using commercially available 4-inch activated carbon combination filters to remove ozone in 12 U.S. cities. The circular symbols represent the median and range bars represent the 95% confidence intervals of health functions used in the modeling analysis.

Of the three building types considered in the commercial building analysis, long-term healthcare facilities have the highest potential to improve health in buildings. Demographics are an important consideration since only persons over the age of 65 were considered in the benefits model. This demographic tends to be the most sensitive to ozone-related health outcomes, particularly premature respiratory mortality. In fact, greater than 90% of the benefits are attributed to reduced mortality. The projected number of lives saved annually range from 103 (Houston) to 195 (Riverside) per 100,000 people. The modeling results indicate that activated carbon filtration in commercial buildings, especially long-term healthcare facilities, would be extremely beneficial in reducing exposures to ozone and should be considered as a strategy to improve public health. Further details on the commercial modeling results are presented in Appendix B.

One of the most important takeaways for the modeling of commercial buildings is that the energy penalty results in a relatively small contribution to the overall cost of carbon filtration. For example, in a baseline condition for a medium sized commercial office building, 7-12% of the total cost of filtration is attributed to the additional energy required due to pressure drop as shown in Table 6.

The baseline modeling condition for commercial office buildings assumed standard pricing for electricity charges during the summer ozone season, however, many utility providers charge demand pricing to commercial customers during the summer when electicity usage is highest. To explore the effect of demand pricing, the summer demand charges for commercial customers in Austin, TX was determined and compared to the baseline charge per kWh used in the previous analysis (Figure 8). As an approximation, the percent difference was then applied to all twelve cities to determine the additional costs due to demand pricing in the summer. A second application included demand pricing and also assumed that the combined HVAC system efficiency (drive, motor, and shaft) was 25% versus the 46% used previously. As shown in Table 6, the energy penalty peaks at 27% of total filtration costs when considering demand pricing and low HVAC system efficiency. Even in the most expensive scenario and city, the benefit-to-cost ratio exceeds 7.0.

Table 6. Health benefits and filtration costs per building when using 2-inch activated carbon filtration in a medium sized commercial office building.

		Seasonal Activated Carbon Filtration Costs (2-inch filter) for Medium Commercial Office Building					
		Baseline Filtration		Filtration with Demand Pricing		Demand Pricing + Low HVAC Efficiency	
City	Health Benefits per Building	Total Costs	Energy Costs (%)	Total Costs	Energy Costs (%)	Total Costs	Energy Costs (%)
Atlanta	$6,419	$690	8%	$718	12%	$787	19%
Austin	$6,617	$680	7%	$711	11%	$773	18%
Buffalo	$7,980	$721	12%	$765	17%	$871	27%
Chicago	$6,641	$680	7%	$703	10%	$760	17%
Cincinnati	$8,020	$685	7%	$711	11%	$773	18%
Houston	$4,532	$681	7%	$703	10%	$759	16%
Miami	$6,290	$690	8%	$718	12%	$787	19%
Minneapolis	$5,875	$686	7%	$711	11%	$774	18%
New York	$6,298	$721	12%	$764	17%	$871	27%
Phoenix	$8,516	$685	7%	$711	11%	$773	18%
Riverside	$9,198	$705	10%	$741	14%	$829	24%
Wash. DC	$7,060	$700	9%	$734	14%	$815	22%

The results presented in Table 6 reflect that the additional cost of the carbon filter (compared to a standard particle filter) and the disposal costs ($17 per filter) dominate the overall costs of carbon filtration. This topic will be more pertinent for 4-inch (or thicker) filters as the pressure drop (and corresponding energy penalty) will be substainally less.

4. FIELD STUDY METHODS AND RESULTS

4.1. Experimental Methods

Indoor air quality and energy usage due to reduced ventilation rates in a laboratory building on the University of Texas campus were measured. The building selected for this study had laboratory space with very high air exchange rates (as high as 12/hr), as well as sophisticated ventilation control and data collection systems.

The laboratory building used in this study is a 142,000 square foot research facility that was constructed in 2008, and certified as LEED Silver. It has six primary floors with the top floor acting as the mechanical space for the facility. The first floor is entirely below grade and the second floor is partially below grade. The building has nine air-handling units and 102 separate laboratory heating, ventilating, and air conditioning (HVAC) zones. In addition, all exhaust air from the laboratories in the building is collected and directed through a glycol heat recovery system. The recovered exhaust heat is then used to pre-heat outdoor air before it passes through the heating and cooling coils in the air-handling unit. Ventilation can be remotely controlled and monitored using a building automation system (BAS) (Siemens Insight BAS Software, version 3.13). A photo of one the teaching laboratories and sampling equipment used in the study is shown in Figure 9.

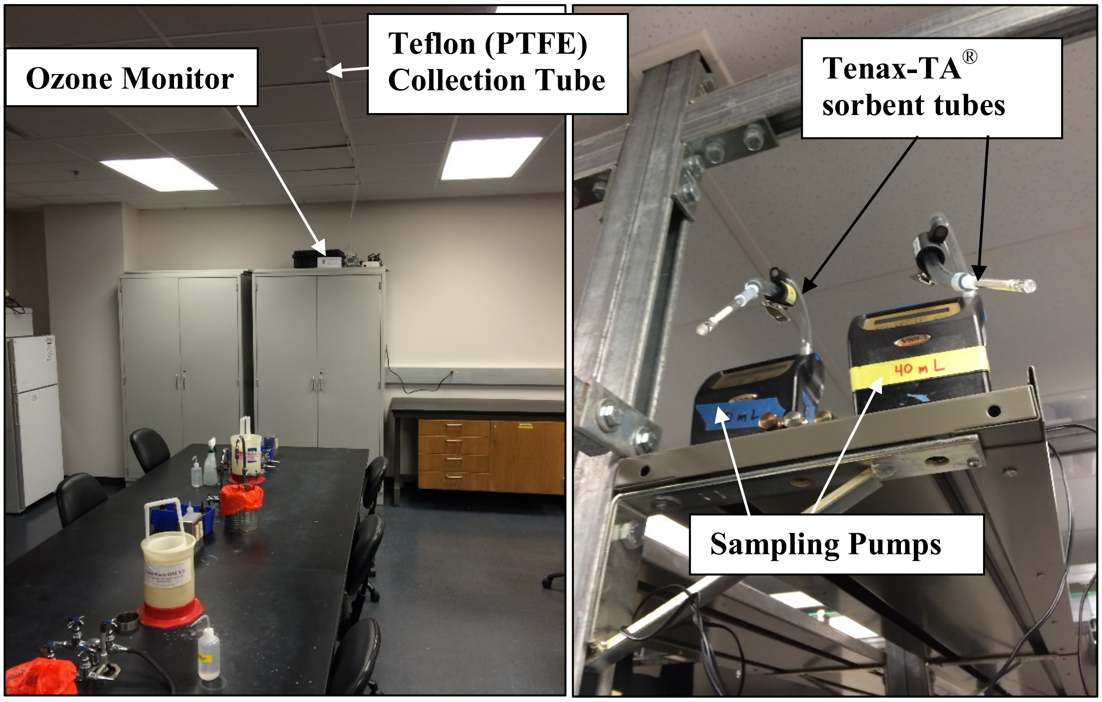

Figure 9. Photos of teaching laboratory and air sampling equipment (L) and of active sampling for VOCs using Tenax-TA® sorbent tubes (R).

Indoor air quality measurements were collected over a course of three weeks under three different testing scenarios: high ventilation, low ventilation, and low ventilation with carbon filtration. Primary pollutants of concern were ozone and volatile organic compounds (VOCs).

Volatile organic compounds were collected using Tenax-TA® with thermal desorption and gas chromatography/mass spectrometry (Hewlett-Packard gas chromatograph model number 5890 II outfitted with a HP 5971 mass selective detector). Each sorption tube was packed with 75 mg of Tenax-TA® sorbent and conditioned in nitrogen at 300°C for two hours. Active sampling was conducted with two pumps in each room during each ventilation condition (Buck Elite-5 Pump 5-6000cc/min 120V). The pumps were programmed at two different pumping rates, 10 mL/min and 40 mL/min, and the sampling time was 4 hours. For every 10 Tenax-TA® samples collected in the field, a lab blank and trip blank were used for baseline analysis. Compounds were identified by using the library compound search in Hewlett Packard's ChemStation software and the NIST 11 Mass Spectral Database. The mass of the identified compounds was estimated using 4-bromofluorobenzene as an internal standard and an assumed response ratio of 1.0. Samples were collected using a sampling rate of 25 mL/min for four hours and were collected in accordance with U.S. Environmental Protection Agency (USEPA) methods (TO-17). In addition to sorption tubes, VOCs were also assessed using summa canisters evaluated by an independent laboratory. The summa canister samples were collected for 24-hours using USEPA method (TO-15).

Ozone concentrations were measured with two UV-absorbance ozone analyzers (2B Technologies Inc., Model 202) programmed to ten minute averaging intervals. Both analyzers were cross calibrated before sampling using a calibrated ozone source (2B Technologies Inc, Model 306) and three point calibration. The indoor ozone measurements were collected using a 6 meter piece of PTFE tubing (Fisher Scientific, ¼-inch O.D., 3/8-inch I.D.), which was positioned with the inlet 30 cm below the ceiling in the center of the room. The second ozone analyzer collected outdoor ozone concentration data in the air-handling unit fresh air intake. Outdoor ozone measurements were also collected from the CAMS 3 air quality monitor in northwest Austin (TCEQ, 2014) to compare against ozone measurements collected in AHU-1. The CAMS 3 air quality monitor is about five miles (line of sight) from the university campus.

Due to low concentrations of VOCs in the laboratories, a total VOC (TVOC) concentration was used to quantify VOC concentration. Concentrations of TVOC were estimated using the total mass under the chromatographic spectra curve from a retention time of 6 to 16 minutes, and then using the molecular weight of toluene to convert from the mass concentration to a volumetric concentration expressed in parts per billion by volume (ppbv).

Ozone and VOC measurements were also collected in the air-handling unit to compare indoor measurements with an outdoor baseline. A photo of the air monitoring equipment positioned in the air-handling unit is presented in Figure 10. Further details on the experimental methods are presented in Appendix C.

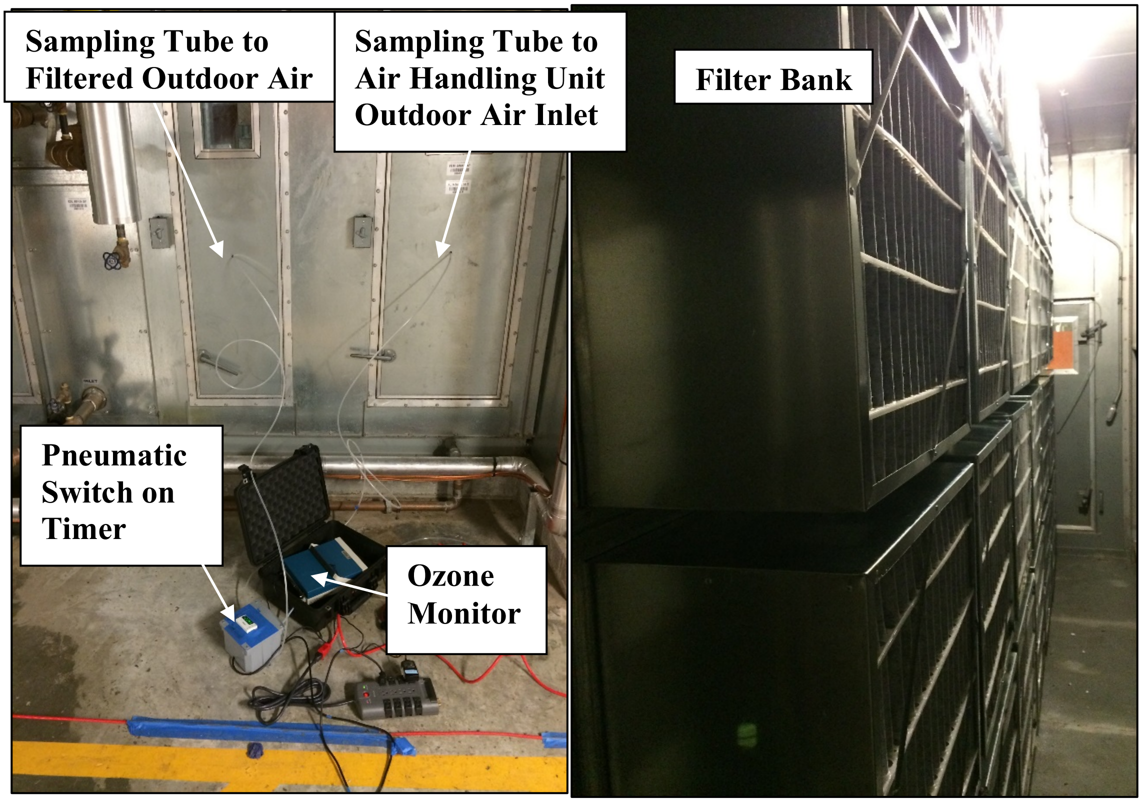

Figure 10. Photo of air sampling equipment in the laboratory building air handling unit (L) and the filter bank with carbon filters installed (R).

4.2. Results and Analysis

In the absence of indoor sources, lower ventilation rates should generally lead to a lower indoor/outdoor (I/O) ozone concentration ratio. However, in this study the I/O ozone concentration ratio (Figure 11) increased by an average of 23% ($\rho < 0.05$) under the reduced ventilation scenario, and the average indoor ozone concentration across the five rooms increased by roughly 10 parts per billion or 56% ($\rho < 0.05$).

The increase in ozone in the laboratories under reduced ventilation conditions is surprising given that ozone has more time to react with indoor surfaces at a lower air exchange rate. The higher ozone concenctration might be attributed to several factors that outweigh the increased reaction time. These include decreased ozone deposition to surfaces caused by the lower air velocity in the room, increased role of ozone sources, e.g., photocopy machines, at lower air exchange rates, or differences in pressure distribution that leads to more ozone entering the study zone from other building zones at lower air exchange rates.

When the activated carbon filters were installed in the air-handling unit at a low ventilation condition, the average indoor/outdoor ozone concentration ratio decreased by 45% ($\rho < 0.05$) compared to the low ventilation condition without carbon filters. The average single pass removal efficiency for ozone through the carbon filters was 70%. The indoor/outdoor ozone concentration ratio was on average 33% lower ($\rho < 0.05$) with the carbon filters installed compared to the high ventilation condition without activated carbon filtration. These results demonstrate that activated carbon filters are effective at reducing indoor ozone concentrations. Potential benefits in a laboratory building include reduced exposure of occupants to both ozone and its reaction products, as well as a reduction of any adverse outcomes of ozone reactions as reported previously in Apte et al. (2008).

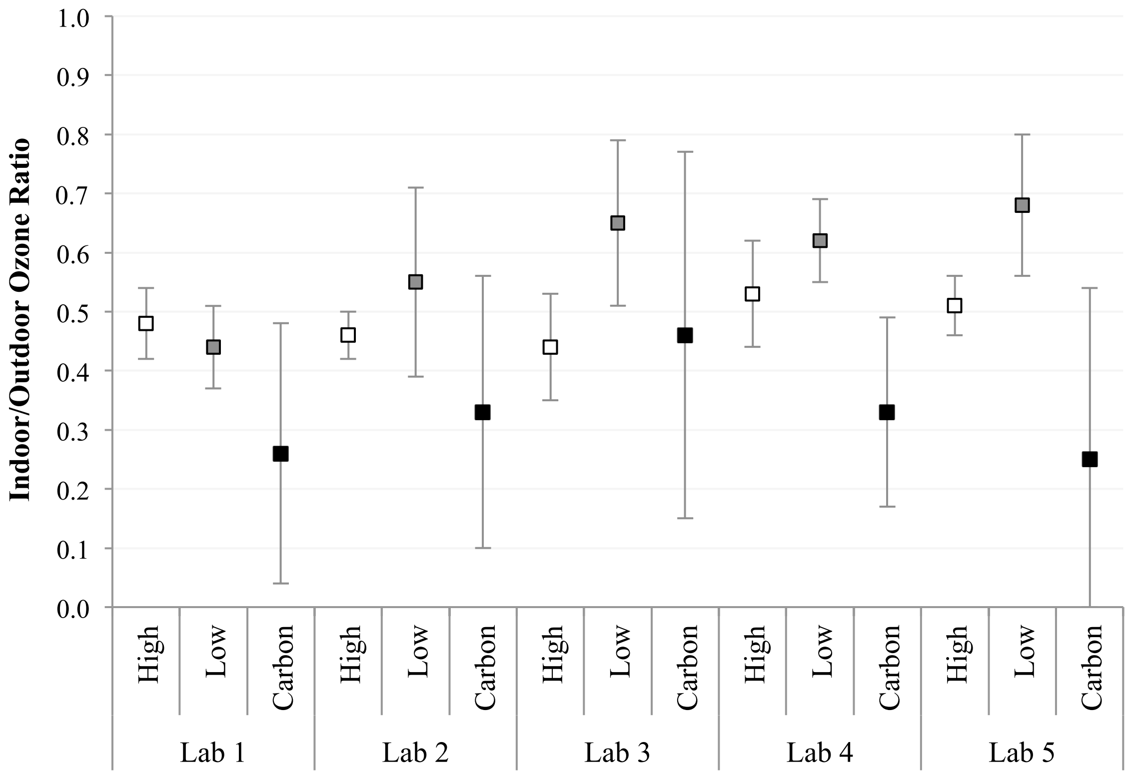

Figure 11. Indoor/outdoor ozone concentration ratios in five sample laboratories building three testing conditions.

Quantification of individual VOCs using Tenax-TA sorbent was difficult because of the low concentrations of VOCs in the laboratories. Therefore, a total VOC (TVOC) concentration was used to quantify VOC concentrations for samples collected on Tenax-

TA sorbent tubes. An average increase of 72% ($\rho < 0.05$) from 6.3 ppb to 10.9 ppb in TVOC was observed when the ventilation rate was reduced from the high to low condition. Specific VOCs were identified and quantified in subsequent testing using summa canisters and TO-15 collection methods analyzed by an independent laboratory. The three VOCs with highest concentrations included dichloromethane, n-hexane, and toluene. The concentrations of VOCs did not vary considerably between the low ventilation condition and the low ventilation condition with carbon filtration, indicating that most of the VOCs measured during the sampling period were emitted from indoor sources in the laboratories. The highest measured concentrations of VOCs are presented in Table 6 with indicators showing at which ventilation condition the highest measurement was collected.

Table 7. Highest recorded VOC concentrations in five sample labs in the laboratory building.

		Highest Measured Concentration ($\mu g/m^3$)					
Volatile Organic Compound	CAS Registry Number	Lab 1	Lab 2	Lab 3	Lab 4	Lab 5	Outdoor
Chloromethane	74-87-3	0	1^{LV}	1^{LV}	2^{LV}	2^{LV}	2^{LV}
Acetonitrile	75-05-8	2^{LV}	1^{LV}	1^{LV}	1^{LV}	0	0
Dichloromethane	75-09-2	19^{LV}	10^{LV}	9^{LV}	3^{LC}	7^{LV}	7^{LV}
2-Butanone (MEK)	78-93-3	0	3^{LV}	3^{LC}	2^{HV}	0	2^{HV}
n-Hexane	110-54-3	14^{LV}	8^{LV}	5^{LV}	9^{LV}	5^{LV}	4^{LV}
Cyclohexane	110-82-7	0	0	6^{LC}	4^{HV}	0	0
Toluene	108-88-3	3^{LV}	28^{LV}	29^{LV}	2^{HV}	6^{LV}	3^{LV}
Tetrahydrofuran	109-99-9	0	0	0	0	0	3^{LV}

HV = High Ventilation
LV = Low Ventilation
LC = Low Ventilation with Carbon Filters

Summa canisters were also collected before and after the bag filters and the carbon filters during the low ventilation condition. The bag filters were sources of TVOCs with an outlet (post filter) TVOC concentration 17% higher than the inlet (pre-filter) concentration ($\rho < 0.05$). The carbon filters removed VOCs and the outlet (post filter) concentration was 62% lower than the inlet (pre-filter) concentration ($\rho < 0.05$). The measured VOCs before and after each type of filter are presented in Figure 12.

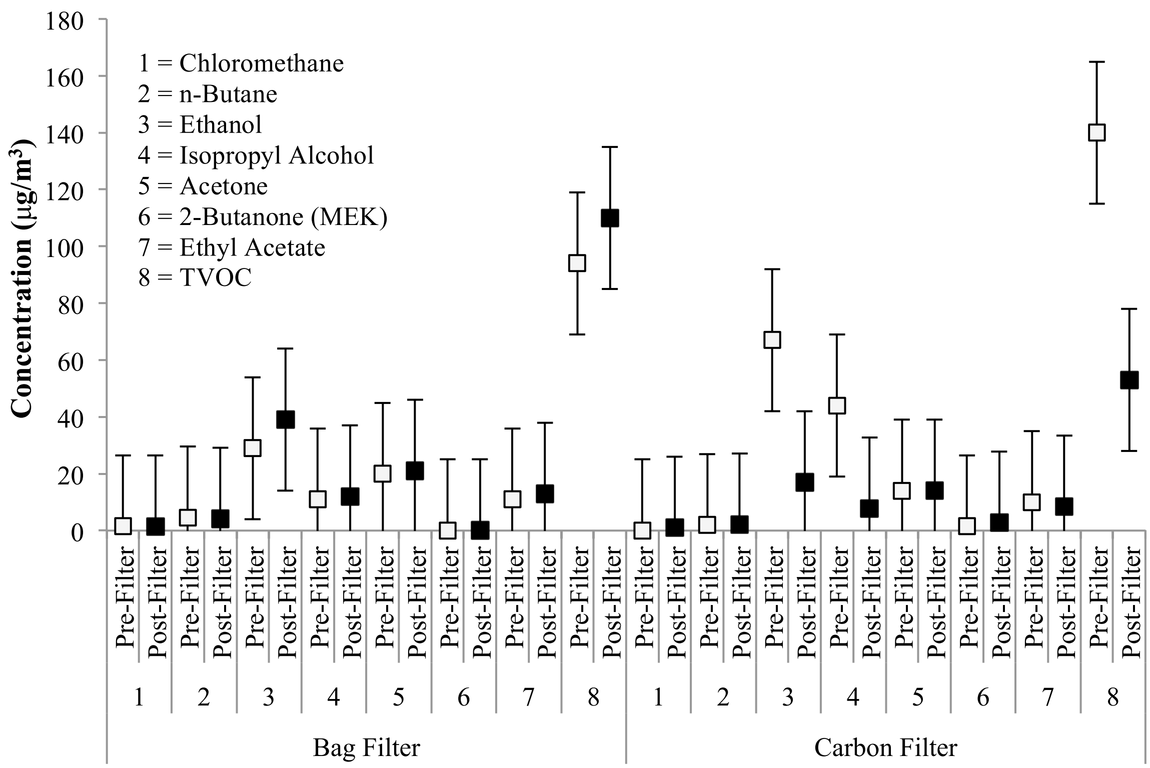

Figure 12. Measured concentrations of VOCs before and after a typical bag filter (L) and an activated carbon filter (R).

The bag filters were a source of VOCs and did not remove ozone. In contrast, the carbon filters were effective at removing outdoor ozone and VOCs, indicating that carbon filters could provide additional health benefits due to VOC removal.

5. FILTER TESTING EXPERIMENTAL METHODS AND RESULTS

5.1. Experimental Methods

Two different commercially available activated carbon filters marketed for odor removal in single-family homes were tested in a laboratory test system. Both filters were new filters and were tested in a clean test system. The filters had dimensions of 51 cm by 64 cm by 3 cm (20 inches by 25 inches by 1 inch). The first filter was composed of activated carbon fibers with 29 grams of carbon in the filter. The carbon in the first filter was applied as slurry and attached to polyester fibers using adhesive. From this point, this filter will be referred to as the activated carbon slurry filter. The second filter was composed of a pleated pre-filter to remove particles followed by a suspended mesh of polyester fibers containing 190 grams of bulk carbon approximately 1-2 mm thick. From this point on, the second filter will be referred to as the bulk activated carbon filter. Filters were tested in triplicate at two different flow rates for two hours. The two test flow rates were 850 m^3/hr (500 cfm) and 1,700 m^3/hr (1000 cfm).

The test system was a closed loop system composed of stainless steel duct material. Air was moved through the test system using two standard 5-ton residential air handling units with tested flowrates varying from 0 to 2500 m^3/hr (0 to 1500 cfm). Each air handling unit utilized a variable frequency drive that allowed for power adjustment from 0% to full power. Seams in the stainless steel duct material were sealed with aluminum tape to reduce leakage in the system. The flowrate through the system was measured with a flow station (Shortridge Instruments, Inc., VelGrid) located at the outlet of air handling unit #2. The pressure difference in the flow station was measured with a digital manometer (Energy Conservancy DG-700 manometer) and converted to a flowrate in cubic feet per minute using a calibrated air flow monitor (Energy Conservancy TrueFlow Plate). The pressure drop across the filter was also measured using a digital manometer (Energy Conservancy DG-700) and pressure drop was recorded at the beginning and end of the two-hour test cycle. The average pressure drop and standard error were calculated from five successive instrument readings during every measurement. A schematic of the laboratory test system is presented in Figure 13.

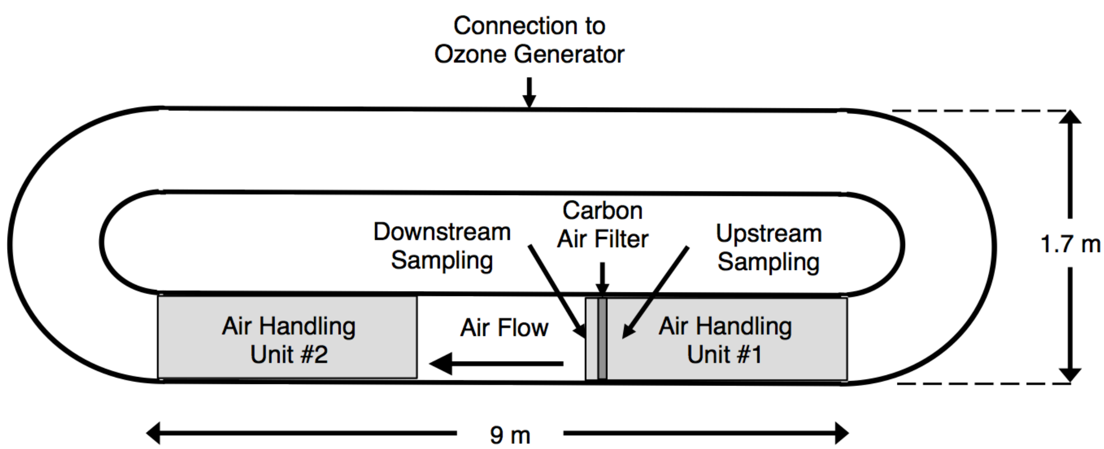

Figure 13. Schematic of the laboratory test system for activated carbon filters.

Ozone concentrations were measured with two UV-absorbance ozone analyzers (2B Technologies Inc., Model 202) programmed to one minute averaging intervals. Both analyzers were cross calibrated before sampling using a calibrated ozone source (2B Technologies Inc, Model 306) and three point calibration. Ozone measurements were logged every minute over the two hour test cycle. Ozone was measured before and after the activated carbon filter using two sampling points connected to the ozone analyzers using a 30 cm (12 inch) piece of PTFE tubing (Fisher Scientific, ¼-inch O.D., 3/8-inch I.D.). The collection tubes were extended through the sheet metal duct and into the test system so that the inlet offset the inner surface by 5 cm (2 inches). This was done in order to avoid boundary level effects on measuring ozone within the test system. Additionally, the collection tubes were offset from either side of the filter by 30 cm (12 inches) in order to reduce errors in ozone measurement due to turbulence before and after the filter. Finally, an ozone generator (Yanco Industries, Ltd., OL-80 Ozone Generator) was used in the laboratory test system to maintain a steady-state inlet ozone concentration of 50 ppb (+/- 10 ppb) at the pre-filter sampling point. Photos of the ozone generator and test system are shown in Figure 14. Estimated ozone generation rates for the activated carbon slurry filter were 19.6 mg/hr (low flowrate) and 28.9 mg/hr (high flowrate). For the bulk activated carbon filter, the estimated ozone generation rates were 42.5 mg/hr and 73.1 mg/hr for the low and high flowrates, respectively.

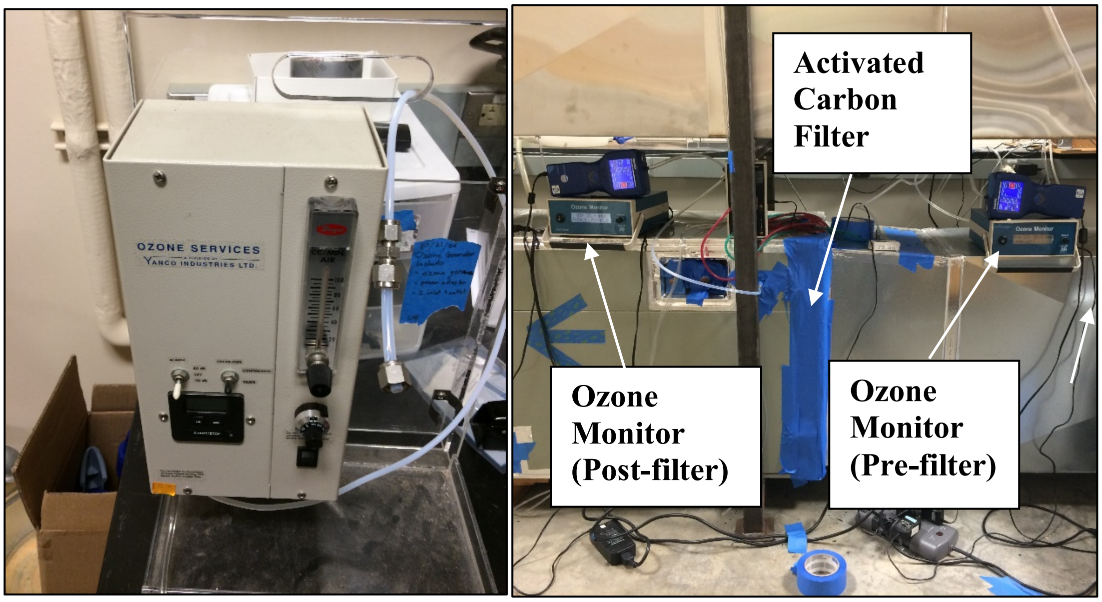

Figure 14. Photo of the ozone generator (L) used in the test system to maintain a steady-state inlet ozone concentration. Ozone was measured before and after the carbon filter (R) using two ozone analyzers.

The single pass removal efficiency of the activated carbon filter was determined by using the pre-filter and post-filter ozone measurements and Equation 7.

$$\eta = 100 \times \left[1 - \frac{C_{O3\,(post-filter)}}{C_{O3\,(pre-filter)}}\right] \quad \textbf{(7)}$$

Where,

η = single pass removal efficiency of the carbon filter (%)
C_{O3} (post-filter) = ozone concentration on outlet side of the carbon filter (ppb)
C_{O3} (pre-filter) = ozone concentration on inlet side of the carbon filter (ppb)

The standard error of each single pass removal efficiency measurement was estimated using error propagation and the measurement error of each ozone analyzer (2 ppb).

5.2. Results and Analysis

Key metrics analyzed in the laboratory study include flow rate through the filter, pressure drop across the filter, and single pass removal efficiency for ozone. Flowrate versus pressure drop for both filters are presented in Figure 15. The error bars in the figure display the standard error of the collected measurements.

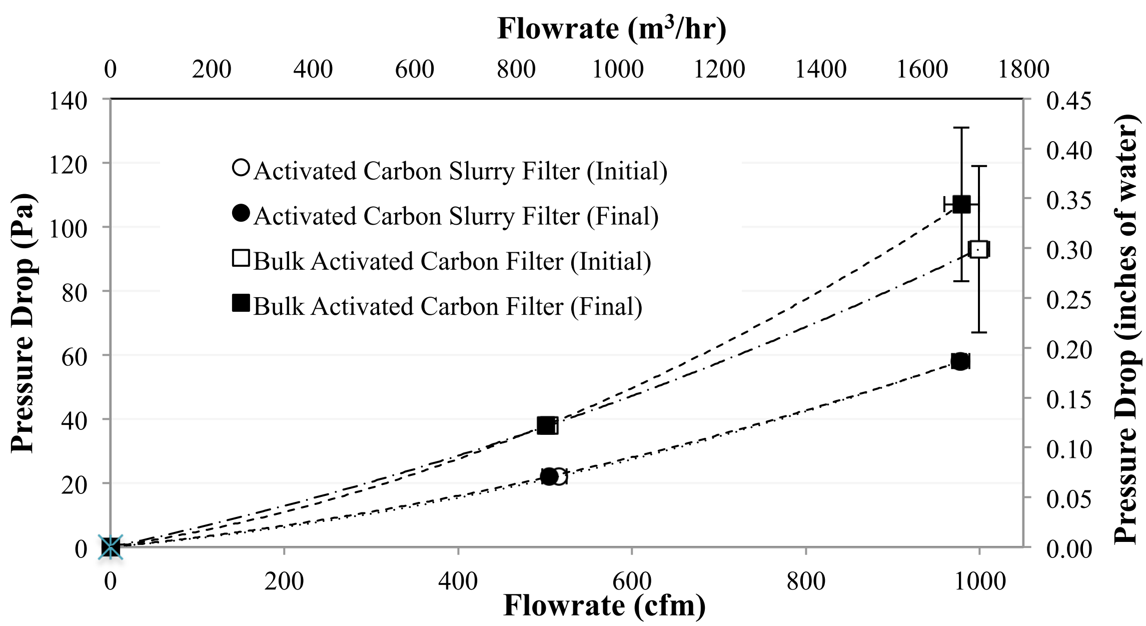

Figure 15. Pressure drop versus flow rate measurements for two commercially available activated carbon filters. Measurements were collected at the beginning and the end of a two-hour test cycle.

The measurements of pressure drop at the high flow rate for the bulk activated carbon filter have a large variance compared to the measurements of pressure drop at the low flow rate. Additionally, there is a noticeable difference between the initial and final pressure drop measurements for the bulk activated carbon filter. This is likely due to deformation within the filter at a high flowrate. The activated carbon slurry filter had a steel reinforcement mesh embedded within the filter and the filter showed nearly no deformation after two hours of operation. In comparison, the bulk activated carbon filter showed noticeable deformation after two hours of operation and this is likely causing some additional error in the pressure drop measurement.

When evaluating the single pass removal efficiency, both filters maintained consistent removal efficiencies over the two-hour test cycle. Both filters had slightly higher single pass removal efficiencies at the lower flowrate. This is consistent with previous research on ozone reactions with activated carbon. Stephens et al. (1986) found that the reaction probability between ozone and carbon declined at higher flowrates. This is likely a result of a longer residence time in the filter at lower flowrates. The lower flowrate through the filter enables the ozone molecules more time to physically adsorb to or chemically react with the carbon surface. The activated carbon slurry filter had an average single pass removal efficiency of 23% (σ = 5%) at the lower flowrate, while the bulk activated carbon filter had an average single pass removal efficiency of 50%. (σ = 6%). The single pass removal efficiencies for both filters are shown in Figure 16.

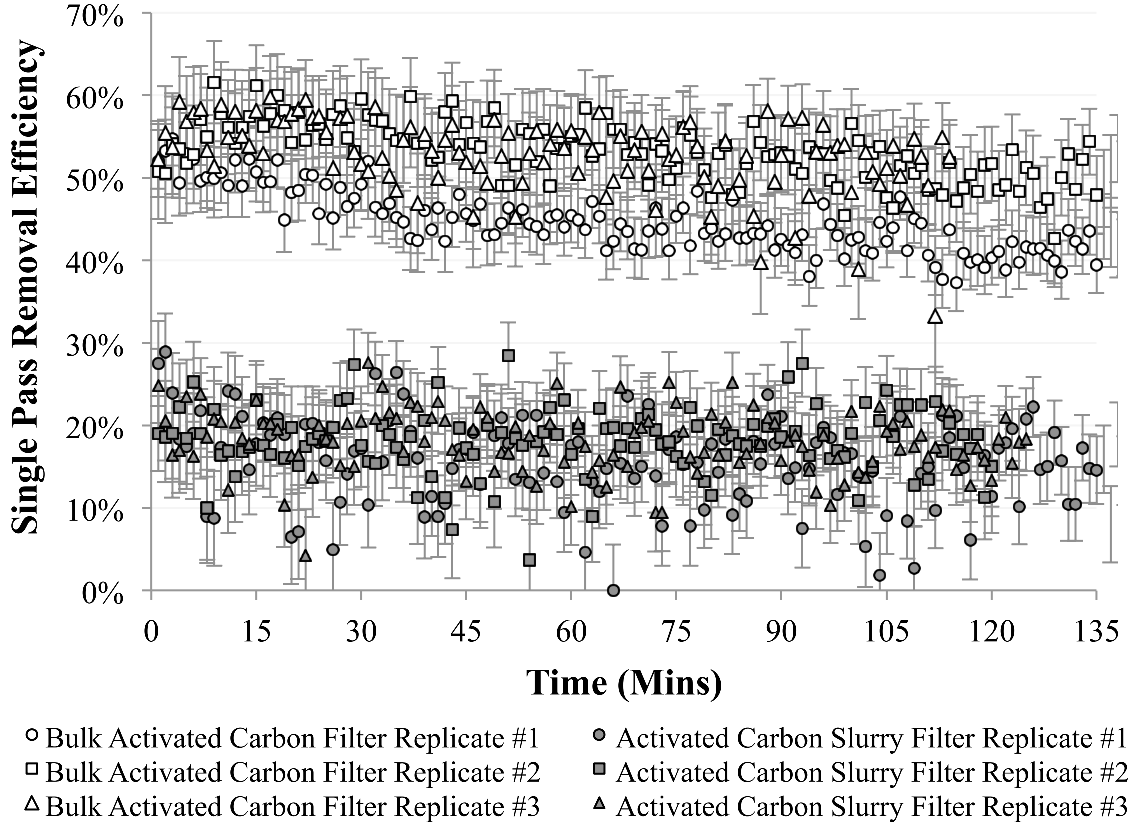

Figure 16. Single pass removal efficiency for ozone for two commercially available activated carbon filters at a flow rate of 850 m^3/hr (500 cfm) for two hours. The error bars represent the standard error due to measurement error.

At the high flowrate (1,700 m^3/hr), the activated carbon slurry filter had an average single pass removal efficiency of 17% (σ = 5%) and the bulk activated carbon filter had an average single pass removal efficiency of 43%. (σ = 6%). The single pass removal efficiencies for both filters are shown in Figure 17.

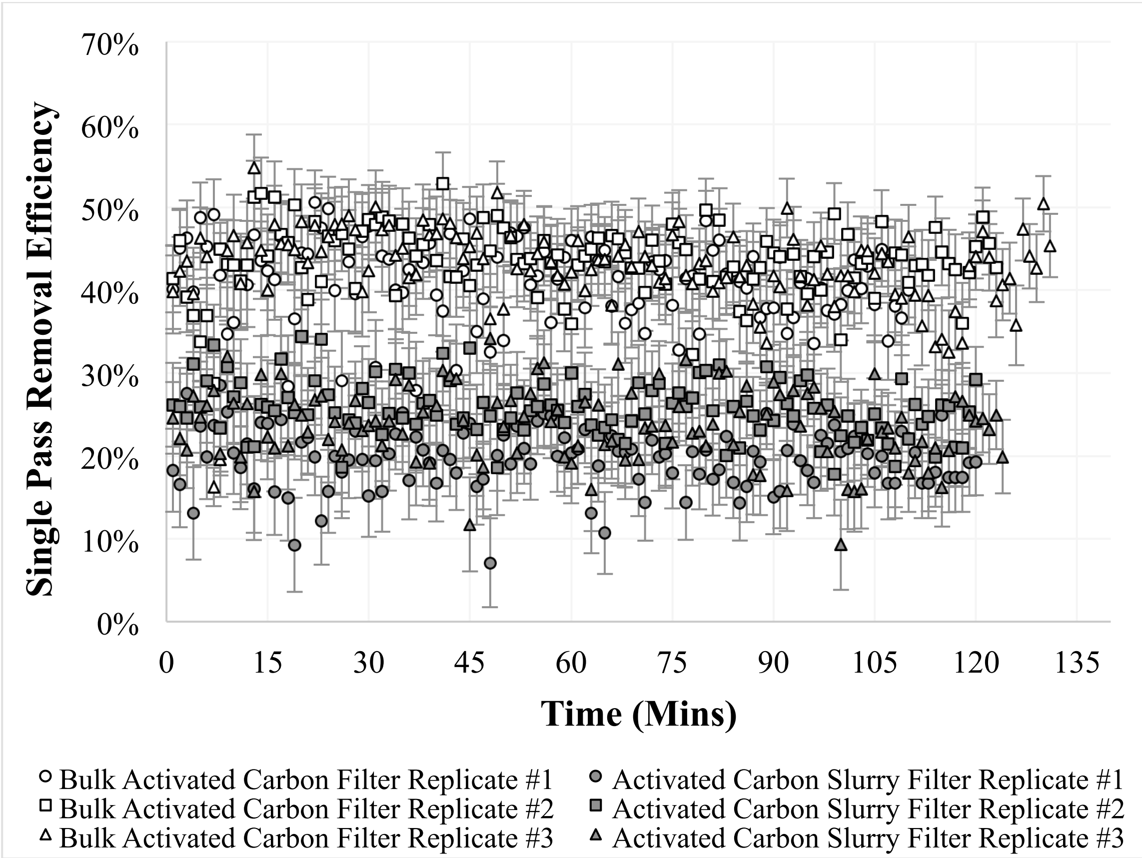

Figure 17. Single pass removal efficiency for ozone for two commercially available activated carbon filters at a flowrate of 1,700 m^3/hr (1,000 cfm) for two hours. The error bars represent the standard error due to measurement error.

As shown in Figures 16 and 17, the bulk activated carbon filter maintains a single pass removal efficiency of 40% over the two-hour test cycle at both the high and low flowrates. The long-term performance of the filter warranted further investigation as ASHRAE Standard 62.1 requires activated carbon filters to have a minimum initial single pass removal efficiency of 40% for ozone removal (ASHRAE, 2013). A long-term test was conducted to determine how the bulk activated carbon filter would perform over time at a constant exposure to 50 ppb of ozone at a flowrate of 2,550 m^3/hr (1,500 cfm). The amount of ozone ultimately removed by the filter is of particular interest and can be calculated using Equation 8.

$$\sum_{t=0}^{\eta=0} mass\ ozone\ removed = \sum_{t=0}^{\eta=0} \eta C_{O3} H_{on} Q \Delta t \qquad \textbf{(8)}$$

Where the mass of ozone is in grams and,

η = single pass removal efficiency of the activated carbon filter at time step t_i (%)

C_{O3} = ozone concentration into the filter (g/m^3)

H_{on} = HVAC hourly cycling operation (-)

Q = flowrate through the filter (m^3/hour)

Δt = time step (hour)

It was determined that the bulk activated carbon filter would remove ozone up until 48 hours of operation. Using the relationship in Equation 8, the total mass of ozone removed by the filter was approximately 23 mg during the 48-hour test cycle. A figure showing the single pass removal efficiency and cumulative mass of ozone removed over time is presented in Figure 18.

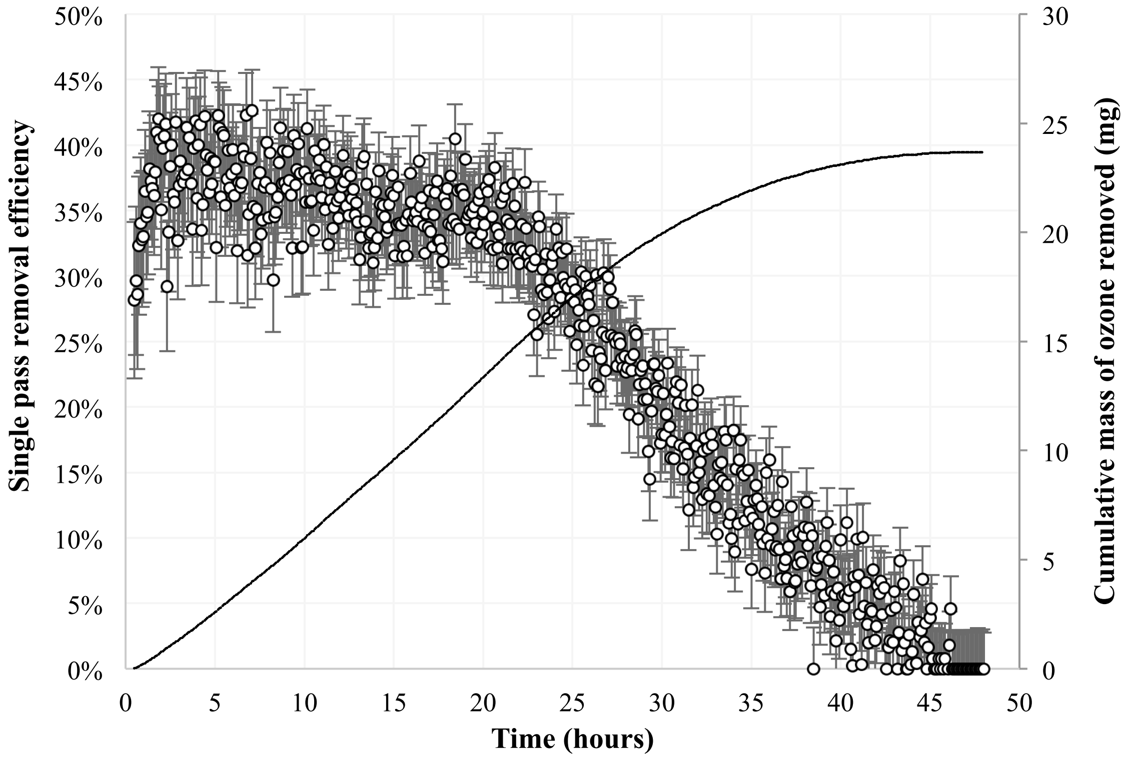

Figure 18. Single pass removal efficiency and cumulative mass of ozone removed for the bulk activated carbon filter at a flow rate of 2,550 m3/hr (1,500 cfm) for 48 hours. The error bars represent the standard error due to measurement error.

The ozone removal capabilities of the bulk activated carbon filter began to significantly deteriorate after 20 hours of constant operation. At 20 hours of operation, the single pass removal efficiency was approximately 35% and quickly dropped to below 30% after 24 hours of operation. After 20 hours of operation, 13 mg of ozone had been removed through the filter (57% of total ozone removed) and 16 mg of ozone had been removed after 24 hours of operation (70% of the total ozone removed). A relationship between the cumulative mass of ozone removed through the filter versus single pass removal efficiency was estimated using the data from the filter experiments and is shown in Figure 19. This relationship predicts the degradation of the filter as it removes ozone over time, which can be useful for modeling applications.

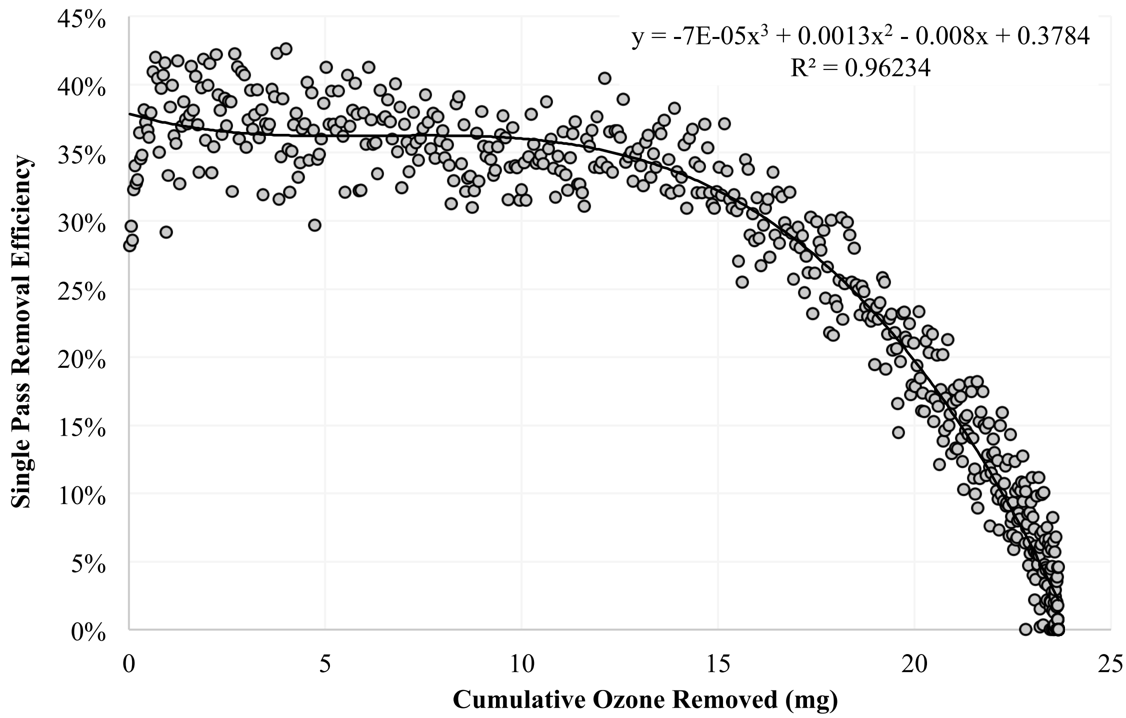

Figure 19. Relationship between mass of ozone removed through the filter and the single pass removal efficiency. As more ozone is removed through the filter, the single pass removal efficiency declines.

Cetin and Novoselac (2015) evaluated 189 newer homes (built since 2008) in Austin, TX and determined average HVAC runtime fractions during the cooling season for every hour of the day. Using their HVAC cycling data, hourly ozone monitor data for the 2014 ozone season (TCEQ, 2014), and Equation (1), the performance of the carbon filter was estimated for six modeling scenarios in a typical single-family home in Austin, TX. All modeling scenarios assumed that the typical Austin home had a volume of 500 m^3, an infiltration air exchange rate of 0.5/hr, and an ozone penetration factor of 0.8. Additional parameters for each modeling scenario are shown in Table 7.

Table 8. Parameters for six modeling scenarios of a typical single-family home in Austin, TX.

Modeling Condition	**Recirc. Flowrate** (m^3/hr)	**Ozone Surface Decay** [AC on] (/hr)	**Ozone Surface Decay** [AC off] (/hr)	**100% fan operation when outdoor ozone > 30 ppb**	**100% fan operation when home is occupied**
Baseline	2,720	5.4	2.8	No	No
Baseline, low reactivity	2,720	2.8	1.5	No	No
Baseline, fan on during high ozone	2,720	5.4	2.8	Yes	No
Baseline, fan on during high ozone, occupied	2,720	5.4	2.8	Yes	Yes
100% fan operation when occupied	2,720	5.4	2.8	No	Yes
100% fan operation when occupied, low reactivity	2,720	2.8	1.5	No	Yes

Filter performance was estimated at hourly intervals and time-stepped using the HVAC cycling data from Cetin and Novoselac (2015), hourly outdoor ozone (TCEQ, 2014), Equation (8), and the relationship in Figure 19. The model predicted ozone reactions with the carbon filter and the cumulative mass of ozone removed since the filter was installed. The cumulative mass of ozone removed by the filter was then used to predict the single pass removal efficiency of the filter at the next time step and the process was repeated for the entire ozone season (1 May to 30 September) as shown in Figure 20.

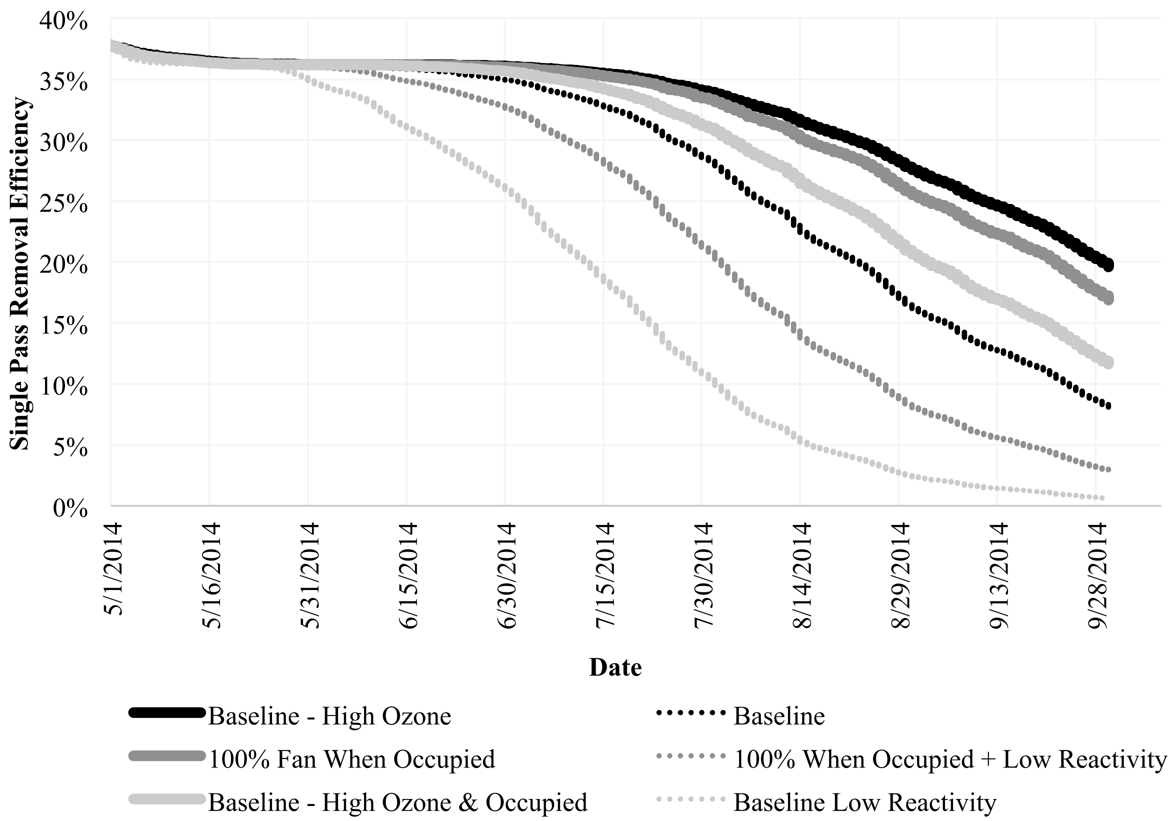

Figure 20. Predicted single pass removal efficiency of activated carbon filter during the ozone season (1 May – 30 September 2014) in a typical single-family home in Austin, TX using six different modeling scenarios.

Using the data from Figure 20 and assuming that the home is not occupied from 8am to 6pm daily, the average ozone exposure in the home was determined for each modeling scenario and compared to a condition with no carbon filtration. Despite the degradation of the filter over the summer, the average residential ozone exposure decreased from 15% to 39%. This is a considerable reduction in exposure, especially when considering that the average person spends about 70% of their lifetimes in their homes. An illustration comparing the average ozone exposure under the six modeling scenarios is shown in Figure 21.

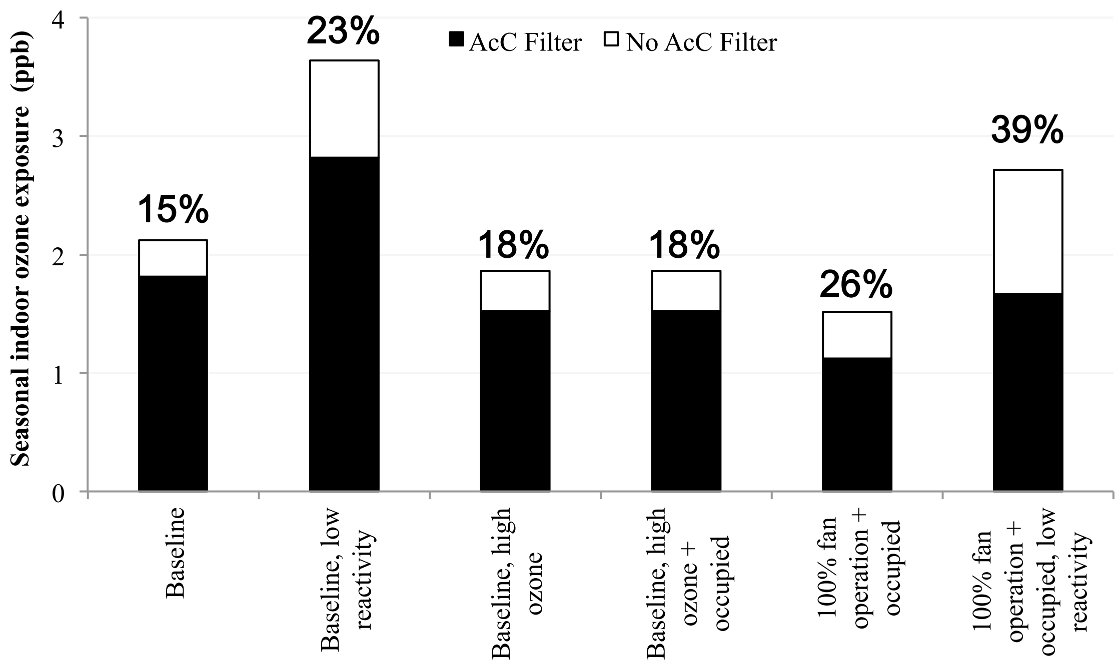

Figure 21. Average ozone exposure in a single-family home when applying activated carbon filtration across six modeling scenarios. The data labels show the percent reduction in ozone exposure when compared to a standard particle filter with no ozone removal.

The reductions in ozone exposure for each modeling scenario where then entered into the systems model (Equations 3, 4, 5, and 6) along with the pressure drop data for the bulk activated carbon filter (Figure 13). It was estimated that at flowrate of 2,720 m^3/hr (1,600 cfm), the additional pressure drop of utilizing the bulk activated carbon filter versus a standard particle filter was approximately 165 Pascal (0.66 inches of H_2O). It was also assumed that the additional cost of the bulk activated carbon filter was $10 more per filter than a standard particle filter. Finally, it was assumed that the electricity costs in Austin, TX were $0.12 per kWh and that the HVAC unit had an overall (drive, motor, shaft) efficiency of 25%. An additional analysis was conducted to see if the benefit-to-cost (B/C) ratio would increase significantly if the pressure drop were reduced 50% and if the activated carbon filter were to be the same price as a standard particle filter. The calculated energy costs due to pressure drop across the filter were 80% to 90% of the overall costs of activated carbon filtration. During the testing of the bulk activated carbon filter, it was very evident that the filter was deflecting during operation, likely increasing the pressure drop across the filter. This was likely due to the absence of steel reinforcing that is common in typical particle filters. It was assumed that a 50% (or more) reduction in pressure drop could be achieved by reducing the deflection of the filter with reinforcement. It was also expected that the costs of activated carbon filters would reach parity with standard particle filters as they become more popular with consumers. The results of the economic analyses for the bulk activated carbon filter are shown in Figure 22.

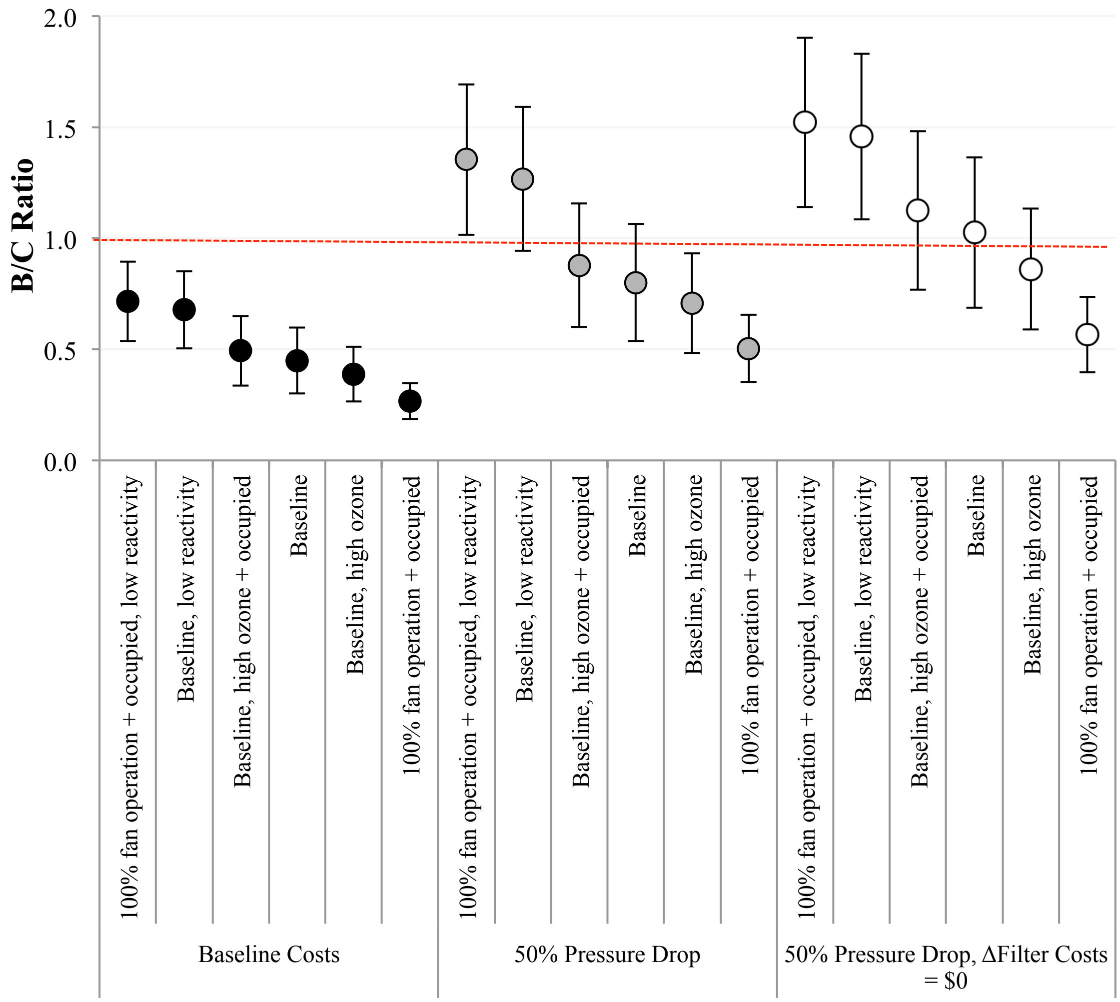

Figure 22. Predicted B/C ratios for six modeling scenarios and three cost configurations. The solid circle represents the mean B/C ratio and the error bars represent the 95% confidence intervals.

As shown in Figure 22, none of the six modeling scenarios had a B/C ratio greater than 1.0 when using baseline costs. When considering a 50% decrease in pressure drop across the filter, the modeling scenarios with low ozone reactivity had B/C ratios greater than 1.0. This is likely attributed to more ozone removal through the filter at the same energy costs as the parallel modeling conditions at baseline reactivity. When the pressure drop across the filter is decreased by 50% and the additional filter cost is zero (i.e., parity with standard particle filter), the baseline condition has a B/C ratio of 1.3. Additionally, five of the six modeling scenarios have error bars that exceed 1.0 indicating that the most sensitive populations would still benefit from residential activated carbon filtration.

These results demonstrate that commercially available activated carbon filters could be beneficial in homes, especially if the pressure drop and additional filter costs are reduced. In nearly every case, it was determined that carbon filtration would be beneficial and economically feasible for the most sensitive populations. This implies that persons with existing respiratory conditions such as chronic obstructive pulmonary disorder and asthma should consider purchasing activated carbon filters for their homes to reduce ozone-related health outcomes. In doing so, they may also benefit economically due to improved quality of life and reduced medical expenses.

Future work should include testing activated carbon filters that had accumulated dust during operational use. Investigating the ozone removal capabilities of dust and deposited chemical compounds may result in higher long-term ozone removal efficiencies of carbon filters.

6. CONCLUSIONS

This chapter includes a brief summary of the overall project effort, major findings, limitations, potential strategies to increase adoption of carbon filtration in buildings, and recommendations for future work (path forward).

6.1. Summary of Research Effort

The overall objective of this research was to complete an assessment of the potential benefits and costs associated with commercially available activated carbon filters. A systems model was developed to determine the costs and benefits of activated carbon filtration in multiple types of buildings. Model parameters were based on a number of sources. These included an intensive search for, and review of, journal articles in the peer-reviewed literature, conference papers, government reports, and technology manufacturer websites. Analysis of resulting data allowed for a "state-of-technology" assessment related to activated carbon filters.

6.2. Major Research Findings

Major research findings are presented below.

1. In-duct ozone removal is currently dominated by activated carbon filtration. However, most carbon filter applications are generally marketed for control of volatile organic compounds (VOCs) and/or odors, and not for control of ozone.

2. Commercial building applications dominate the activated carbon filter market and are typically marketed for industrial control of gaseous pollutants.

3. Filter systems vary substantially in design, ranging from non-woven pleats that contain activated carbon to V-bank trays and cassettes that contain granular activated carbon.

4. Pleated activated filters appear to be the most common for non-industrial applications or applications that do not require more costly systems. Most of these pleated filters are hybrid (combination) systems for removal of both particulate matter and gases.

5. Activated carbon filters are currently of marginal benefit for residential applications across most cities, with the exception of Riverside, California, and Phoenix, Arizona, where the B/C ratios are relatively high. The B/C ratio increases with higher outdoor ozone concentration, greater fractional operation time of HVAC systems, and older

populations with higher respiratory disease prevalence.

6. There are additional conditions for which activated carbon filtration becomes more viable in residential settings, including increased occupancy and the presence of sensitive individuals. For these special cases the use of activated carbon filtration in residences appears to be beneficial and worthy of consideration in most cities at this time.

7. For residential buildings, continuous fan operation during the summer ozone season (assuming an Electronically Commutated Motor is available) can significantly increase ozone removal effectiveness. The B/C ratio for such conditions is also substantially increased for cities that would otherwise have relatively low HVAC operation during the ozone season (e.g., Buffalo, Chicago, Minneapolis, New York City), but is only slightly increased for other cities.

8. In general, across target cities the benefit/cost ratio for 1-inch filters is somewhat lower than for 2-inch and 4-inch filters (the three depths studied herein) due to higher differential pressure drops and associated energy costs between 1-inch AcC and conventional particle filters. The B/C ratio is generally slightly lower for 4-inch than 2-inch filters due to higher differential costs for the former.

9. The benefits of activated carbon filtration in commercial (office) buildings are much greater than in residential buildings (B/C several times higher) across all target cities. Application of activated carbon filters to office buildings appears to be viable at this time.

10. The benefits of activated carbon filtration in K-12 schools are much higher than for residences, and such applications appear to be viable at this time. The dominant benefit in terms of reduced DALYs comes in the form of prevented school loss days.

11. The benefits of activated carbon filtration in long-term health care facilities are substantial (higher than for other building types that were considered in this study) and should be considered for adoption at this time. The dominant benefit in terms of reduced DALYs stems from reduced mortalities and reduced hospital admissions due to chronic respiratory diseases.

12. The B/C ratio for activated carbon filters is sensitive to the differential cost between activated carbon and particle filters. It is very likely that as demand for activated carbon filters increases the cost differential will decrease, making their applications even more attractive in the future.

13. In absolute terms, the additional cost (e.g., relative to a standard particle filter) of activated carbon filtration in single-family homes for the summer ozone season is

approximately $10 per person or $25 per household. For a 1-inch activated carbon filter in use during the summer ozone season, approximately 60% of the filtration cost is attributed to the energy penalty due to additional pressure drop. Future research should focus on investigating the operational pressure drop of activated carbon filters, especially in single-family homes. Actual energy pentalties may be much lower than predicted because of lower flowrates through the filter, resulting in the economical use of activated carbon filters in single-family homes during the summer ozone season.

6.3. Limitations of Research

This research was the most rigorous to date with respect to assessment of the benefits and costs of activated carbon filtration for ozone control in buildings. Nevertheless, research was limited in several ways.

1. The published and available gray literature related to long-term performance of activated carbon for removal of ozone, particularly under the highly-variable environmental conditions often encountered in practice, is sparse. For this study, existing data were sufficient to develop preliminary assessments of ozone removal effectiveness in residential and commercial buildings.

2. Average ozone concentrations across a five-month ozone season were used in this analysis. In turn, the health effects following high/peak ozone events were not

captured. Indoor ozone control during such events would increase the benefit/cost ratios described in this dissertation, particularly for sensitive populations.

3. Indoor ozone concentrations are typically much lower than outdoor ozone concentrations, even without specific ozone control technologies. In this study we assumed that there is no threshold below which incremental reductions in indoor ozone concentration do not have a positive health effect. This is an important issue that has yet to be effectively resolved by the health science community. If a threshold is found to exist above typical indoor ozone concentrations the benefits described in this dissertation might be substantially reduced. Importantly, if a threshold does exist it will be dependent on averaging time and lowest for long-term averages such as those used in this study.

4. The health effects of indoor secondary organic aerosols (SOA) are not well defined and related predictions were largely omitted from this study. The same is true of many other ozone reaction products, including many carbonyls, di-carbonyls, carboxylic acids, peroxides, and more. In turn, the predicted health benefits in the systems model may underestimate the overall health benefits of ozone removal via activated carbon filtration.

5. Sources of indoor ozone were not included in this study. Such sources may be important in offices or schools with poorly maintained and highly operated photocopy

machines and/or laser printers, or in residences or other buildings in which ion generators or electrostatic precipitators are used for particle control. For such scenarios the benefit/cost ratio of activated carbon filtration will increase.

6. In this study, the benefits and costs of ozone control are characterized entirely in economic terms that are supported by reference to published literature. This requires that reductions in physical suffering, e.g., from asthma, be quantified in a way that reflects average societal values, and not necessarily those of individuals who suffer the most from exposure to ozone. There are costs, both social and health, that are difficult to impossible to quantify with any degree of accuracy. Those who have the economic resources to spend more for health benefits may choose to do so. But there is also a bias against those for whom the required marginal costs are impractical to pay. These factors are difficult to capture and were not incorporated into the systems model. As such, it is expected that the results presented herein underestimate the overall benefit/cost ratio associated with ozone control, particularly for sensitive sectors of the population.

7. On the cost side of the systems model, there is a substantial uncertainty related to HVAC system efficiency. In this study, the worst-case scenario (i.e., use lower boundary of HVAC system efficiency) was generally assumed. However, in discussions with HVAC subject matter experts the combined system efficiency used for commercial buildings (including long-term healthcare facilities and K-12 schools)

may be higher than values used in this study. This concern was addressed by running another analysis and assuming a lower HVAC system efficiency. The results are presented in Table 6. The analysis showed that the capital costs of the filters (additional cost compared to standard particle filter plus disposal costs) dominated the total cost of carbon filtration. Even in the worst-case scenario (demand charges plus 25% system efficiency), the highest energy penalty contributed to 27% of the total cost of carbon filtration in a medium sized commercial office building. Despite the higher energy costs, the B/C ratio of using carbon filtration still exceeded 7.0. Although there is some uncertainty in HVAC system efficiency, the overall effect on total filtration costs is minor, especially for 2-inch and 4-inch filters. Future research should explore and measure the energy penalties of carbon filters in a large population of operational buildings to determine the true impact on overall filtration costs.

8. The effects of carbon filtration on the microbiome of the built environment were not considered in this research and the impacts on the microbiome are unknown at this time. This topic should be investigated in greater depth in future research projects involving activated carbon filtration in HVAC systems.

6.4. Strategies to Improve Indoor Health with Activated Carbon Filters

A major research objective was to recommend potential strategies and policies to utilize activated carbon filtration for ozone removal in buildings. The results of this research indicated that carbon filtration in commercial office buildings, long-term healthcare facilities, and K-12 schools during the summer ozone season (1 May to 30 September) would be beneficial. A revision of standards such as ASHRAE Standard 62.1 could result in widespread adoption of carbon filters in urban areas with high seasonal ozone. Additionally, credentialing programs administered by organizations such as ASHRAE and the U.S. Green Building Council could offer a path to incentivize installing carbon filters in buildings.

Many of the health benefits gained by removing ozone in indoor environments could be considered preventive care and could also improve worker productivity. A wellness collaboration between health insurance companies and employers could incentivize installing activated carbon filters in commercial office buildings, especially in companies that are self-insured and directly bear the financial burden of employee medical costs. In fact, lost productivity due to health impairments can cost a company $1,400 to $2,600 per employee annually (Henke et al., 2010). Previous research predicted that strategies to improve indoor air quality in commercial office buildings could result in improved worker productivity resulting in benefit-to-cost ratios of 5 to 116 over a 20-year period (Wargocki and Djukanovic, 2005). In all of the modeling scenarios in their research, the typical pay back for improved indoor air quality strategies was less than two years with an average rate of return of 12.4-21.6%.

The performance of corporate wellness programs have been thoroughly researched primarily because of the rising costs of medical care (Kelly et al., 2010). In one case study examining best practices in two self-insured manufacturing companies, investments in ergonomics and safety interventions resulted in a benefit-to-cost (B/C) ratio exceeding 10:1 (Hantula et al., 2001). In another recent study involving more than 12,000 corporate wellness participants, the wellness program had an overall B/C ratio of 2.48 and the B/C ratio exceeded 9.0 when only evaluating the benefits of preventative health risk assessments (Musich et al., 2015). Finally, in an 8-year study of a corporate wellness program, the long-term B/C ratio averaged 2:1 and participants who had stayed enrolled for the entire eight years reduced their annual healthcare expenses by 36% (Schwartz et al., 2014). Average costs to the company ranged from $204 to $288 per participant per year and annual medical costs were nearly $1,600 less per year compared to non-participants.

The predicted costs of activated carbon filtration in commercial office buildings averages less than $0.50 per month per employee. In turn, the company realizes nearly $17 of health benefits per employee during the ozone season. Additional health and productivity benefits will be gained due to the removal of volatile organic compounds through the carbon filter and the reduction of ozone reaction products such as formaldehyde and acetaldehyde. Therefore, a small investment in activated carbon filters could result in substantial health and productivity benefits for companies and will pay for itself within one ozone season.

Strategies for residential carbon filtration include using behavioral economics concepts as default bias and social norms (Stevens, 2014). A strategy incorporating default bias could involve medical practicioners supplying patients with filters during office visits in conjunction with follow up visits and health assessments to determine if the filter was installed and if the filter resulted in any health benefits. Strategies involoving social norms have been fairly successful and include strategies such as wearing helments on bikes and using seat belts while driving (Steven, 2014).

Incentivizing carbon filtration can also be a strategy for higher adoption rates in single-family homes. Nearly a dozen studies were recently funded by the Affordable Care Act to evaluate Medicaid incentive programs to improve health and encourage healthy behaviors (Blumenthal et al., 2013). Incentive programs included cash incentives and vouchers for medical-related expenses. A similar strategy could be implemented to offset the cost of a residential carbon filter, especially in households that have members with pre-existing respiratory conditions.

6.5. Research Path Forward

An important outcome of an assessment study is the identification of areas for future research. Several future research areas are listed below.

1. Rigorous lab and field testing are needed to confirm, and expand on, the performance of activated filters over a wide range of operating and environmental conditions in actual buildings. Important metrics that should be measured over operational time include single-pass ozone removal efficiency, pressure drop and air flow rate (and incremental energy costs), and (if possible) improvements in occupant health, productivity, and learning performance (for schools).

2. The systems model or other models should be modified and used to assess the benefits of indoor ozone control during peak ozone events.

3. The systems model should be used for enhanced evaluation of the benefits and costs of ozone control in buildings, perhaps including a wider range of carbon filter technologies, building types and cities. With proper parameter distributions Monte Carlo simulations might also be useful for elucidating fractional population benefits and costs of activated carbon filtration.

4. Existing data related to reaction product yields and health effects associated with organic nitrates stemming from $NO_3^{\bullet}$ chemistry preclude it from being further

considered for quantitative assessment in this study. However, given its potential importance to human health we believe that nitrogen oxide chemistry should be incorporated into future benefit/cost analyses related to ozone control, particularly when data can reasonably support quantitative estimates of reaction products and their impacts. In addition, we recommend altering the systems in the future to analyze other air contaminants in the indoor environment.

Appendix A

PAPER I

Benefit-Cost Analysis of Commercially Available Activated Carbon Filters for Indoor Ozone Removal in Residential Buildings

(Submitted to *Indoor Air*)

Abstract

This study involved the development of a model for evaluating the potential costs and benefits of ozone control by activated carbon filtration in single-family homes. The modeling effort included the prediction of indoor ozone and ozone reaction products with and without activated carbon filtration in the HVAC system. As one application, the model was used to predict benefit-to-cost ratios for single-family homes in 12 American cities in five different climate zones. Health benefits were evaluated using the disability-adjusted life-years attributed to the difference in indoor ozone concentration with and without activated carbon filtration and included city-specific age demographics for each simulation. Costs of commercially-available activated carbon filters included capital cost differences when compared to conventional HVAC filters of similar particle removal rating, energy penalties due to additional pressure drop, and regional utility rates. The average indoor ozone removal effectiveness ranged from 4 to 20% across the 12 target cities, and was largely limited by HVAC system operation time. For the parameters selected in this study, the mean predicted benefit-to-cost ratios for 1-inch filters were greater than 1.0 in 10 of the 12 cities. However, median values for all 12 target cities were below 1.0. The benefits of residential activated carbon filters were maximized in

cities with high seasonal ozone and HVAC usage, suggesting the importance of targeting such conditions for activated carbon filter applications.

Introduction

Exposure to ozone and ozone reaction products is harmful to human health. Ozone reacts with polyunsaturated fatty acids in fluids lining the lung with subsequent adverse effects in the airway epithelium (Levy et al., 2001). Several researchers have shown a link between exposures to ozone and premature mortality (Bell et al., 2005; Ito et al., 2005; Jerrett et al., 2009; Levy et al., 2005; Smith et al., 2009; USEPA, 2006, and references provided therein). Additionally, there have been several investigations that associate ozone exposure and increases in respiratory-related hospital admissions (e.g., Burnett et al., 1999), minor restricted activity days (e.g., Ostro and Rothschild, 1989), and school loss days (e.g., Chen et al., 2000). The USEPA estimates that 265 to 450 lives would be saved per year by reducing the eight hour ozone standard by 5 parts per billion (ppb), resulting in potential annual health benefits of U.S. $7.5 billion to $15 billion (2011 dollars) per year (USEPA, 2014a).

Nearly one third of Americans live and work in counties with ozone concentrations that exceed the primary eight-hour average National Ambient Air Quality Standard (NAAQS) for ozone, which is currently 75 ppb (USEPA, 2014b). The NAAQS for ozone is meant to protect public health, including the health of sensitive populations such as children, people with asthma, and the elderly. Ozone concentrations are typically lower indoors than outdoors, largely due to its reaction with materials in the building envelope, heating, ventilating, and air conditioning (HVAC) system components, building contents, and occupied space (Chen et al., 2012a; Fadeyi, 2014; Fadeyi et al., 2013; Fadeyi et al., 2009; Morrison et al., 1998; Stephens et al., 2012; Wang and Morrison, 2010; Wang and Morrison, 2006; Weschler, 2000). Although ozone concentrations are typically lower indoors than outdoors, Americans spend an average of nearly 90% of their time indoors (Klepeis et al., 2001). This leads to the indoor environment being important with respect to total inhalation exposure to ozone. For example, in a study involving 2,500 residences in seven cities, indoor exposure accounted for 43% to 76% of total daily exposure to ozone, with a mean of 60% (Weschler, 2006). As such, ozone control in single-family homes should be further explored.

Very little epidemiological research has been dedicated to studying the effects of ozone exposure in indoor environments. Instead, most epidemiological research on ozone exposure has relied on ozone measurements taken from outdoor fixed monitors (Bell et al., 2014; Bell et al., 2006; Bell et al., 2005; Bell et al., 2004; Berman et al., 2012; Hubbell et al., 2005; USEPA 2014a; USEPA 2012). However, Chen et al. (2012a) used a simple mass balance model and showed that variations in ozone mortality can be partially explained by the amount of ozone transported into residential buildings through infiltration, windows, and HVAC systems. This finding is consistent with observations that the prevalence of centralized air conditioning systems, which are associated with lower air exchange rates and lower indoor ozone concentrations, is inversely associated with ozone-related mortality (Smith et al., 2009).

In a seminal study of indoor exposure to ozone, Weschler et al. (1989) concluded that indoor exposure to ozone is greater than outdoor exposure for many Americans, and that "relatively inexpensive strategies exist to reduce indoor ozone levels." Given the well-established health and welfare impacts of ozone exposure, it is appropriate to explore the benefits of indoor ozone reduction and the costs of building-scale ozone control. The purpose of this study is threefold: (1) To determine if commercially available activated carbon filters are effective at removing ozone in homes; (2) To determine if using commercially available activated carbon filters is an economically viable strategy to reduce ozone in homes; (3) To determine conditions for which the benefits of residential activated carbon filtration might be particularly high, thus informing public health strategists and standard-setting organizations.

Model Development

The model developed for this project consists of an integrated system that addresses several major components and their interconnections (Figure 1). The integrated model is used to determine the concentration of ozone in buildings and is intended for determining indoor ozone and ozone reaction product concentrations in multiple types of buildings. In this assessment, we are only evaluating ozone-related health benefits when using activated carbon filtration in single-family homes.

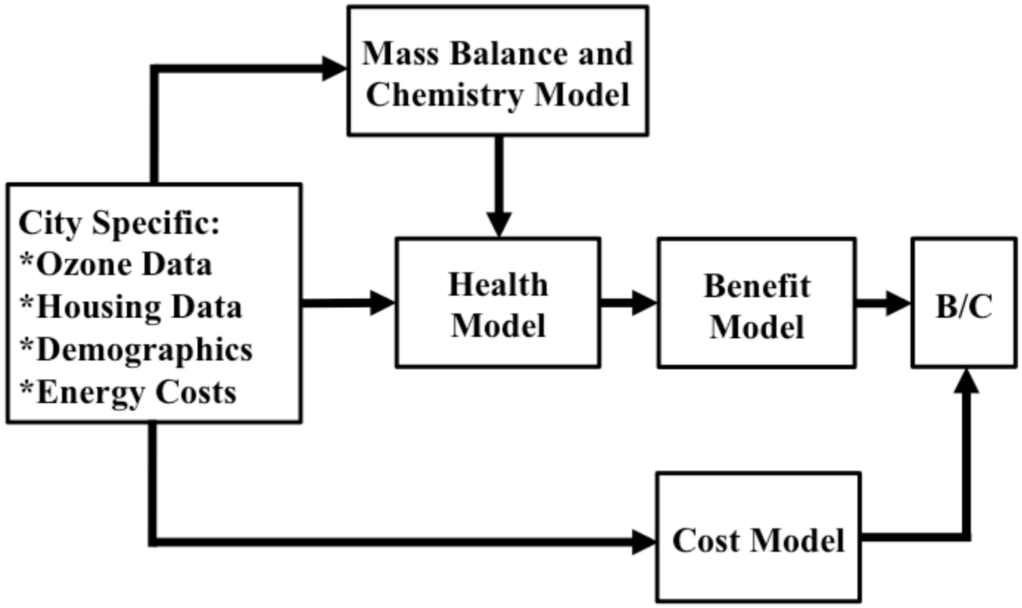

Figure 1. Conceptual model illustrating interconnected sub models of the integrated systems model.

Mass Balance and Chemistry Model

Core model equations are used to solve for ozone concentration and concentrations of several key reaction products as previously presented in Fadeyi (2014), Chen et al. (2012a), and Weschler and Shields (2000). The fate of ozone within a building is estimated using a simplified mass balance equation and assuming a well-mixed environment. The model is designed to estimate concentrations of ozone for scenarios without any control devices and scenarios with control devices in place. The differences in these scenarios are used to quantify the health benefits of ozone control.

The time-averaged mass balance equation for ozone is presented Equations (1). A detailed derivation of Equation (1) is presented in the supplementary information.

$$C_{O3} = \frac{p\lambda_{inf}C_{o,O3}}{\lambda_{inf}+H_{on}\lambda_{rec}f_{c,O3}+(H_{on}k^{*}_{dep,O3,AC_{on}}+(1-H_{on})k^{*}_{dep,O3,AC_{off}})+\sum_j k_jC_j}$$

(1)

Where,

λ_{inf} = infiltration air exchange rate [h^{-1}]

λ_{rec} = recirculation air exchange rate of HVAC system [h^{-1}]

C_j = concentration of gaseous reactant j in the occupied space [ppb]

C_{O3} = concentration of ozone in the occupied space [ppb]

$C_{o,O3}$ = concentration of ozone in outdoor air [ppb]

$f_{c,O3}$ = single-pass fractional removal of ozone by an activated carbon filter [-]

H_{on} = average annual fraction of time that the HVAC system operates [-]

$k^{*}_{dep,O3,AC\_on}$ = ozone decay rate for integrated background surfaces w/ HVAC on [h^{-1}]

$k^{*}_{dep,O3,AC\_off}$ = ozone decay rate for integrated background surfaces w/ HVAC off [h^{-1}]

k_j = bimolecular homogeneous reaction rate constant [$ppb^{-1} \cdot hr^{-1}$]

p = fractional penetration through the building envelope for ozone [-]

Concentrations of common ozone reaction products such as formaldehyde, acetaldehyde, and secondary organic aerosols can also be determined by mass balance equations as shown in the supplementary information.

In a preliminary modeling analysis, the health outcomes for formaldehyde and acetaldehyde were calculated using methods described in Logue et al. (2012) and Huijbregts et al. (2005). However, the initial modeling results indicated that the health benefits of reduced reaction products were greatly outweighed by the benefits of reductions in ozone, on the order of attributing 1% or less of the total overall health benefits. Additionally, the DALYs calculations for formaldehyde and acetaldehyde were determined from animal testing and incorporated a large amount of uncertainty (Huijbregts et al., 2005). In contrast, the ozone-related DALYs were determined from human exposure models and are commonly used in epidemiological analyses (USEPA, 2012b).

Health outcomes for exposure to secondary organic aerosols (SOA) are very uncertain due to the size and composition of the aerosols (Polidori et al., 2007). However, the health effects of ozone-generated SOA exposure may have a higher oxidative capacity than $PM_{2.5}$ that could result in oxidative stress in the pulmonary system (Delfino et al., 2013). Additionally, the small size of SOA may result in a higher penetration into the respiratory tract. This could subsequently lead to the transport of SOA to other organs through the circulatory system (Oberdorster et al., 2010). At this time, it’s difficult to accurately quantify the health benefits of reductions in ozone-generated SOA, however, this could be an important topic to research given the potential health implications. Therefore, due to the uncertainty in determining the health effects of reductions in ozone reaction products, only reductions in ozone due to activated carbon filtration were considered in this analysis.

Ozone Removal Effectiveness

Ozone removal effectiveness is defined as the percent reduction in indoor ozone concentration when an ozone control device is used relative to an identical condition when such a device is not used, as described by Equation (2).

$$\Omega = (1 - C_{AcC}/C_{No\_AcC}) \times 100\% \qquad \textbf{(2)}$$

Where,

Ω = ozone removal effectiveness of activated carbon filter (%)

C_{AcC} = indoor ozone concentration with activated carbon filter installed (ppb)

C_{No_AcC} = indoor ozone concentration without activated carbon filter installed (ppb)

Benefit Model

Benefits are calculated using reductions in disability-adjusted life-years (DALYs) due to reductions in indoor ozone concentration following the application of activated carbon filtration. Disability-adjusted life-years are a metric for quantifying the burden of disease, and incorporate years of life lost from premature mortality and years of life lost from disability due to the incidence of disease. The methodology for determining change in health incidence and the corresponding value of DALYs follows previous work completed by the USEPA (2012, and references provided therein) and others (Logue et al., 2012; USEPA, 2010; Huijbregts et al., 2005). Table 1 presents all of the health functions and parameters used in our analysis for ozone.

Table 1. Health outcomes due to ozone exposure.

Health Outcome	Int'l Disease Code	β *(95% CIs)*	DALYs per Incidence	Sources
Mortality (25 to 34)	J00-J99	0.0045 (0.0015, 0.0074)	27.14	USEPA (2010); Jerrett et al. (2009); USEPA (2012); Lopez et al. (2006)
Mortality (35 to 44)	J00-J99	0.0045 (0.0015, 0.0074)	24.78	
Mortality (45 to 54)	J00-J99	0.0045 (0.0015, 0.0074)	22.42	
Mortality (55 to 64)	J00-J99	0.0045 (0.0015, 0.0074)	18.58	
Mortality (65 to 74)	J00-J99	0.0045 (0.0015, 0.0074)	13.36	
Mortality (75 to 84)	J00-J99	0.0045 (0.0015, 0.0074)	9.64	
Mortality (85+)	J00-J99	0.0045 (0.0015, 0.0074)	5.45	
Respiratory Hospital Admission (18 to 64)	460-519	0.0020 (0.0010, 0.0030)	0.03	USEPA (2012); Logue et al. (2012); Burnett et al. (1999); Lvovsky et al. (2000)
Dysrhythmia Hospital Admission (18 to 64)	427	0.0020 (0.0000, 0.0040)	0.03	
Dysrhythmia Hospital Admission (65+)	493	0.0020 (0.0000, 0.0040)	0.03	
Minor Restricted Activity Day (18 to 64)		0.0026 (0.0011, 0.0041)	0.0005	Hubbell et al. (2005); Ostro and Rothschild (1989); USEPA (2012)
School Loss Day (5 to 17)		0.0158 (0.0060, 0.0255)	0.0007	Hubbell et al. (2005); Chen et al. (2000); USEPA (2012)
Respiratory Hospital Admission (65+)	460-519	0.0021 (0.0013, 0.0029)	0.03	USEPA (2012); Moolkavgar et al. (1997); USEPA (2012); Lvovsky et al. (2000)

The change in disease incidence for each modeling scenario is calculated using a baseline condition (no ozone control) and then subtracting the disease incidence when ozone control is applied and lower occupant exposures to both ozone and its reaction products occur (Equation (3). The calculations include parameters for baseline incidence, concentration-response (C-R) functions, DALYs per incidence, and city-specific age populations (USEPA, 2012; USEPA, 2011a; USEPA, 2011b USEPA, 2011c; Logue et al., 2012, US Census Bureau, 2012). The value of y_0 is specific to the disease or health condition being considered and changes depending on the pollutant, health outcome, and age.

$$\Delta\, Incidence = \Sigma\, \Delta\, Incidence_{\mathbf{i}} = \Sigma[\, [y_0 \times (1\text{-}e^{-(\beta \Delta C(freq))})]_{\mathbf{i}} \times population_{\mathbf{i}}] \qquad \textbf{(3)}$$

Where,

$\Delta\, Incidence$ = sum of change in disease incidence across a large population of various age groups **(**$\Sigma\, population_{\mathbf{i}}$**)** [number of disease outcomes]

y_0 = baseline prevalence of disease across a large population of various age groups **(**$\Sigma\, population_{\mathbf{i}}$**)** $\left[\frac{\text{Health Outcomes}}{\text{Population-Year}}\right]$

β = concentration-response coefficient $\left[\frac{\text{Relative Risk}}{\text{Concentration}}\right]$

ΔC = change in pollutant concentration [$\mu g \cdot m^{-3}$]

freq = exposure frequency, or fraction of one year where exposure occurs [-]

Generally, the reduction in indoor ozone concentrations in single-family homes will be relatively small (typically less than 5 ppb) compared to peak outdoor ozone events. We used USEPA methodology to convert peak ozone events to seasonal average concentrations (USEPA, 2012). Additionally, we inquired with a health scientist at the USEPA (Fann, 2014) to determine if any thresholds are used for ozone in USEPA risk assessments. The USEPA does not currently use a threshold for ozone exposure and so we assumed that there would be potential health benefits for small reductions in indoor ozone concentrations.

The number of DALYs per pollution exposure is calculated using Equation (4), and the estimated health benefit across a whole population ($\Sigma\, population_i$) is calculated using Equation (5).

$$\Delta\text{DALYs} = \left[\frac{\text{DALYs}}{\text{Incidence}}\right] \times \Delta Incidence \qquad \textbf{(4)}$$

$$Benefits = \$/DALY \times \Delta DALYs \qquad \textbf{(5)}$$

Where,

Benefit = monetary benefit associated with reduced DALYs per 100,000 people [$]

$/DALY = value of one disability adjusted life year [$$\$\cdot year^{-1}$$]

Δ*DALYs* = reduction in DALYs (relative to no control) when a control is used [years]

When calculating DALYs, the number of years of life lost per mortality is dependent on the age at which mortality occurs (Lopez et al., 2006). The greatest uncertainty in the benefits analysis is attributed to the value of an avoided DALY, more specifically, what the average person is willing to pay to avoid a health-related issue due to ozone exposure. One generally accepted approach is to equate one DALY avoided as approximately equal to three times the per capita gross domestic product (Rascati, 2006). In the United States, this is equivalent to approximately $150,000 (2014 US dollars) per avoided DALY (World Bank, 2014). Bobinac et al. (2014) also evaluated the value of a quality-adjusted life-year (QALY) gained in the Netherlands using a survey incorporating a broad range of ages, incomes, and educational levels. One QALY gained is equivalent to one avoided DALY. Their methods used a weighting factor from Tversky and Kahneman (1992) to integrate decision theory and human behavior under risk. From their survey results, they were able to estimate a probabilistic distribution of what the average person is willing to pay to gain a QALY. Their results indicated a distribution with a mean of approximately $140,000 (2014 US dollars) per avoided QALY.

For this paper, a distribution of dollars per avoided DALY was developed based on Bobinac et al. (2014), and was used to estimate the benefits of reduced exposure to ozone and its reaction products. This method yields lower benefits than the USEPA methodology used in the Regulatory Impact Analysis for ozone (USEPA, 2008). The USEPA uses a value per statistical life (VSL) of approximately $9.3 million (2014 U.S. dollars) per life lost regardless of age at the time of death (USBLS, 2014; USEPA, 2011b). In contrast, the DALYs method assigns a value of life based on the years of life lost compared to the average life expectancy, which results in lower benefits when compared to the USEPA method. Further information on the DALYs calculations and benefit model are provided in the supplemental information.

Cost Model

Overall filter costs include the difference in capital costs (materials and labor) between a standard particle filter and an activated carbon filter, as well as additional energy costs due to the difference in pressure drop between a standard particle filter and an activated carbon filter. Other costs such as installation and disposal are not included in this paper as our analysis focused on commercially available filters designed for residential HVAC systems. Overall filter costs are calculated for a population of 100,000 using Equation (6) and assuming one to two filters per residential HVAC unit during the summer ozone season (1 May through 30 September):

$$Costs = \left[[P_{elec} \times E_{cost}] + [(F_{cost} + L_{cost}) \times (RF)]\right] \times \left[\frac{100{,}000}{Occ.}\right] \quad \textbf{(6)}$$

Where,

Costs = overall differential cost between activated carbon and conventional particle filters (AcC – particle) per 100,000 persons [$]

P_{elec} = seasonal electricity usage [kWh] due to additional pressure drop

$$= \left[\frac{Q_{filter} \times \Delta P_{diff} \times H_{on\_tot}}{1000 \times \eta_{HVAC}}\right]$$

E_{cost} = electricity cost per kWh [$]

Q_{filter} = flowrate through the filter [$m^3 \cdot h^{-1}$]

ΔP_{diff} = difference in pressure drop across the filter between AcC filter and standard filter [Pa]

H_{on_tot} = total number of hours of HVAC operation [hours]

η_{HVAC} = overall efficiency of the HVAC fan and motor [-]

F_{cost} = difference in filter costs between AcC filter and standard particle filter [$] (assumed to equal zero for residences)

L_{cost} = difference in labor, replacement, and disposal costs between AcC and particle filters [$] (assumed to equal zero for residences)

RF = filter replacement frequency [$season^{-1}$]

Occ. = building occupancy [persons] (average varies by city)

City specific electricity costs and HVAC operational runtimes are provided in greater detail in the supplementary information. Overall filter costs are extrapolated for a population of 100,000 in order to compare with DALYs using the same metric (per 100,000 people).

Monte Carlo Simulation

Due to the uncertainty in all of the model parameters, a Monte Carlo simulation similar to models used previously in Gall et al. (2011) and Morrison et al. (2011) were used to estimate changes in indoor ozone concentration with and without activated carbon filters, the difference in DALYs due to changes in ozone exposure, and the benefits and costs of utilizing activated carbon filters in residences during the summer ozone season.

The key metrics used to measure the impacts of activated carbon filters include the ozone removal effectiveness and the B/C ratio. A sensitivity analysis of the systems model was completed to estimate the influence of individual modeling parameters to changes in ozone removal effectiveness and the benefit-to-cost ratio (B/C). Additional details on the sensitivity analysis are presented in the supplemental information.

Model parameters that were assumed to not vary geographically are presented in Table 2. City-specific model parameters are presented in the supplemental information. Distributions were estimated from the references when possible, and in some cases when additional data was not available, distributions were estimated using the mean and standard deviations of data (modeled as normal distributions) reported in the literature. In those cases where only extreme (i.e., minimum and maximum) values were found in the literature, a uniform distribution was assumed.

Table 2. Model parameter characteristics for Monte Carlo simulation.

			Percentile of Distribution							
Parameter	Units	Symbol	0	2.5	25	50	75	97.5	100	Source
Ozone penetration factor	[-]	p	0.24	0.53	0.70	0.78	0.86	0.98	1.00	[1]
Single pass O_3 removal	[-]	$f_{c,O3}$	0.30	0.31	0.35	0.40	0.45	0.50	0.50	[2]
Recirculation rate	h^{-1}	λ_{rec}	2.97	3.19	5.06	7.10	9.62	15.0	22.4	[3]
O_3 surface loss HVAC off	h^{-1}	$k_{dep,O3,AC\_off}$*	0.00	0.52	1.97	2.82	3.70	5.37	8.12	[4]
O_3 surface loss HVAC on	h^{-1}	$k_{dep,O3,AC\_on}$*	0.00	1.05	3.80	5.45	7.12	10.3	15.6	[5]
Homogenous reactions	h^{-1}	$\Sigma_j k_j C_j$	0.06	0.09	0.10	0.11	0.12	0.13	0.16	[6]
Fraction of time indoors	[-]	*freq*	0.23	0.50	0.63	0.70	0.77	0.89	1.00	[7]
Dollars per DALY	$000s	*$/DALY*	0.00	6.94	63.9	125	202	366	691	[8]
Flowrate across the filter	$m^3 \cdot h^{-1}$	Q_{filter}	680	747	1359	2038	271 6	3332	3400	[9]
Additional pressure drop	Pa	ΔP_{diff}	4.52	5.28	14.1	27.5	44.0	61.6	63.7	[2]
HVAC fan and motor eff.	[-]	η_{HVAC}	0.20	0.21	0.27	0.35	0.43	0.49	0.50	[10]
Additional filter cost	$	F_{cost}	0.00	0.50	5.01	10.1	15.0	19.5	20.0	[11]
Filter replacement frequency per season	[-]	*RF*	1.00	1.02	1.25	1.50	1.75	1.97	2.00	[2]

Sources: [1] Stephens et al. (2012), [2] Filter Manufacturer, [3] Stephens et al. (2011), [4] Lee et al. (1999), [5] Sabersky et al. (1973), [6] Corsi et al. (2014), [7] Klepeis et al. (2001), [8] Bobinac et al. (2014), [9] Morrison et al. (2013), [10] Stephens et al. (2010), [11] Rosenthal (2014)

The Monte Carlo simulation inputs from Table 2 were estimated as probabilistic distributions generated from 100,000 random numbers using MATLAB, a commercially available computational software (MathWorks, 2013). An original program was written in MATLAB to perform the comprehensive Monte Carlo simulation. Outputs of the simulation included probabilistic distributions for ozone removal effectiveness, DALYs gained, and B/C ratios for each of the 12 sample cities.

Benefit-Cost Analysis of Carbon Filtration in Single-Family Homes in 12 U.S. Cities

The systems model described herein was used to assess changes in indoor ozone, health incidence, and the B/C ratio for ozone control in 12 U.S. cities. At least two cities from each of the five climate zones defined by the Energy Information Administration were selected for the analysis. The following cities were included in the analysis: Atlanta, Austin, Buffalo, Chicago, Cincinnati, Houston, Miami, Minneapolis, New York City, Phoenix, Riverside, and Washington D.C. This group of cities represents a broad nationwide sample of population, climate, building stock, and ambient ozone concentrations. Housing data for each city were collected from multiple sources, including the American Housing Survey (AHS) (U.S. Census, 2013), Chen et al. (2012a and 2012b), and Persily et al. (2010). Data collected on city-specific summer ozone concentration, electricity costs, HVAC usage, and building characteristics are provided in the supplemental information.

A final modeling simulation incorporated an assumption that all of the ozone-related health outcomes would apply only during the summer ozone season. In the previous analyses, the calculated DALYs were scaled by 5/12 in order to compare the benefits with the associated filter energy costs from 1 May to 30 September. However, in other analyses that incorporate USEPA protocols for determining health outcomes from ozone exposure, the health outcomes for the entire year were assumed to occur during the ozone season. Berman et al. (2012) and Hubbell et al. (2005) used USEPA modeling software to evaluate the potential health benefits of reductions in ambient ozone from 1

May to 30 September in cities across the U.S. The USEPA regulatory impact assessment for ozone (USEPA, 2014b) incorporates health outcome functions that were originally applied to the summer ozone season, and some of the applied ozone controls (e.g., regulating gasoline vapor pressure) are only used during the summer season. The results of the modeling exercise are presented in the supplemental information (Figures S6 and S7).

Results and Discussion

Results for applications of activated carbon (AcC) filters in single-family homes in each of 12 target cities are presented in this section. All analyses correspond to only the summer ozone season, taken to be May 1st to September 30th for each city.

Filter costs were primarily driven by the additional energy costs for 1-inch (2.5 cm) filters due to increased pressure drop. Approximately 60% of the filtration costs were attributed to energy costs, with the remaining costs attributed to the additional cost of the filter in comparison to a standard particle filter.

The ozone removal effectiveness of AcC filtration in single-family homes is presented in Figure 2. Cities with high air-conditioning usage during the ozone season have the highest values of ozone removal effectiveness. The highest base-case effectiveness (approximately 20%) occurs for homes in Miami, and is limited by the frequency of HVAC operation and single-pass ozone removal efficiency for the AcC filter. A single-pass ozone removal efficiency of 60% was assumed based on the lower bound of proprietary field measurements by a filter manufacturer that were taken from homes in both a hot and humid and cold and humid climate. No other values for this parameter could be found in the published literature.

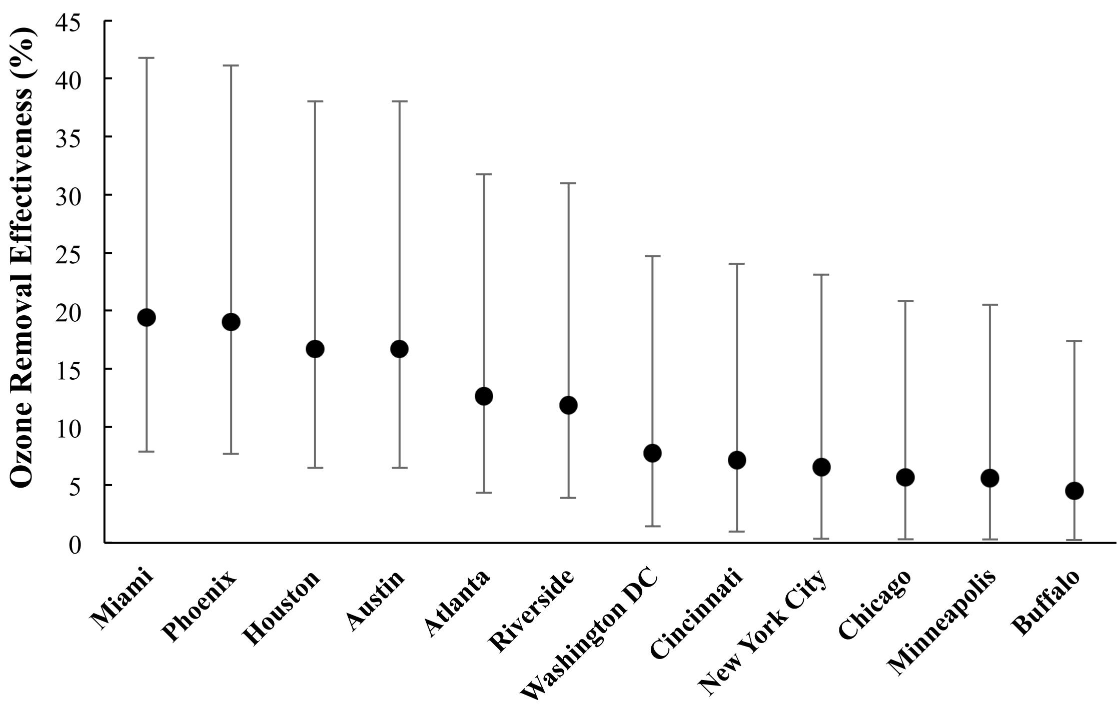

Figure 2. Ozone removal effectiveness of activated carbon filters in homes. The filled circle represents the median set of parameters and the whiskers represent the 95% confidence intervals of the distribution determined by the Monte Carlo simulation.

During the summer ozone season, the predicted average daily indoor ozone concentration for typical homes without AcC filtration is relatively low, generally less than 5 ppb. This is largely due to low average ozone concentrations across the entire ozone season (integrated over all day and night hours). As such, an ozone removal effectiveness of less than 20% leads to very small absolute reductions in averaged indoor ozone concentrations in each target city, i.e., less than 1 ppb. Of course, the outdoor and absolute indoor concentrations and concentration reductions are often much higher (by a factor of 2 to 4) than average values during daily outdoor one-hour or eight-hour peaks. And there are some conditions in homes, e.g., low background reactivity and high air exchange rate, which lead to higher indoor ozone concentrations. Importantly, relatively small reductions (5 ppb) in outdoor ozone concentrations have been shown to yield population-wide health benefits (e.g., Berman et al. 2012; Hubbell et al. 2005). However, the published literature is insufficient to determine ozone concentration thresholds below which reductions in ozone exposure provide tangible health benefits. Our analysis is based on an assumption of no threshold concentration below which health effects are not observed. We note that mortality risk associated with increased outdoor ozone concentrations appears to occur even at low concentrations of tropospheric ozone, with thresholds as low or lower than approximately 10 ppb for 24-hour averages and 20-30 ppb for daily one-hour maximum concentration (Bell et al., 2006; Kim et al., 2004).

Reductions in annual DALYs per 100,000 people are shown in Figure 3, with median values ranging from 1 to 5 DALYs per 100,000 per year. Bounds on health benefits and benefit/cost ratios are based on 95% confidence intervals of health functions and were used to estimate disability-adjusted life years (DALYs) and mortality.

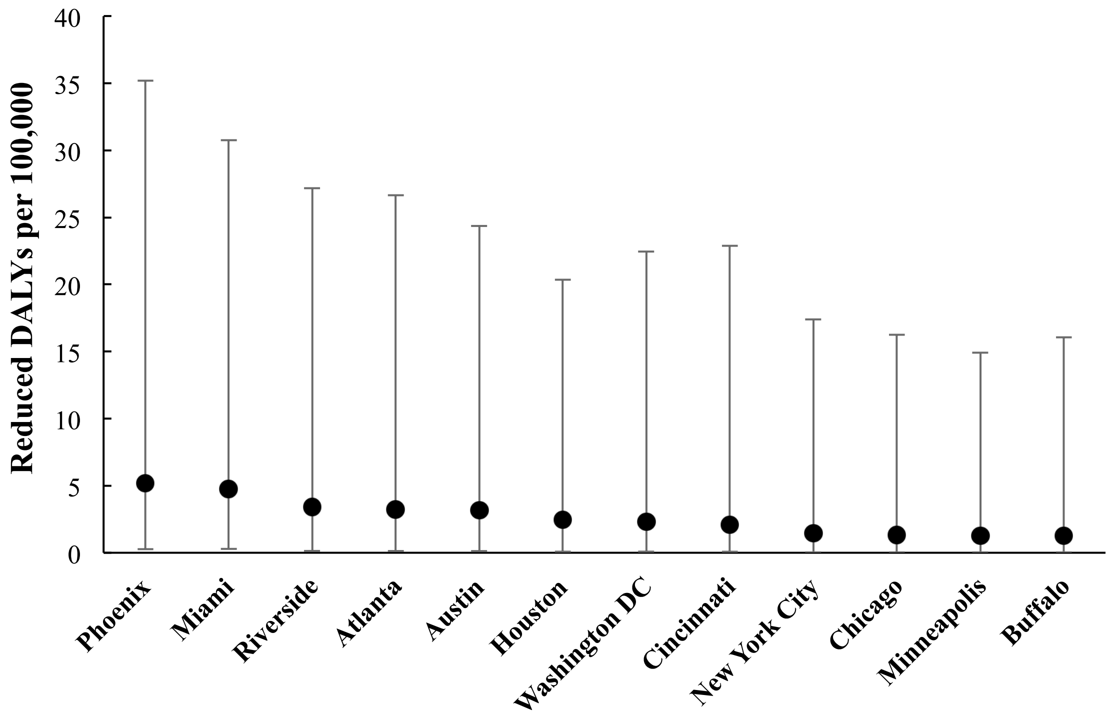

Figure 3. Reductions in DALYs per year from using activated carbon filters in homes. The filled circle represents the median and the whiskers represent the 95% confidence intervals of the DALY parameter distributions determined by the Monte Carlo simulation.

Of the 12 target cities, homes in Phoenix would benefit the most from carbon filtration, followed closely by Riverside (Figure 4). For each of these two cities the mean B/C ratio is approximately 2.0. High summertime ozone concentrations and relatively new building stocks characterize these two cities with high air conditioning usage during summer months. This implies that cities with high summer temperatures (and by extension high air conditioning usage), high summertime ozone, and a high proportion of residential air conditioning usage (implying newer building stock) will benefit the most from residential carbon filtration. Cities that had lower B/C ratios include Buffalo and Minneapolis. These two cities are characterized by a milder summer climate and generally lower air conditioning usage (Chen et al., 2012a). In addition, since both cities have milder climates and older building stock, residents may generally open windows for cooling and may also experience higher rates of infiltration through the building envelope. This is an important consideration for our analysis because the filters can only remove ozone when the HVAC system is operating.. Additionally, cities with older building stock typically do not have central HVAC systems (Chen et al., 2012a), further limiting the benefits of activated carbon filtration.

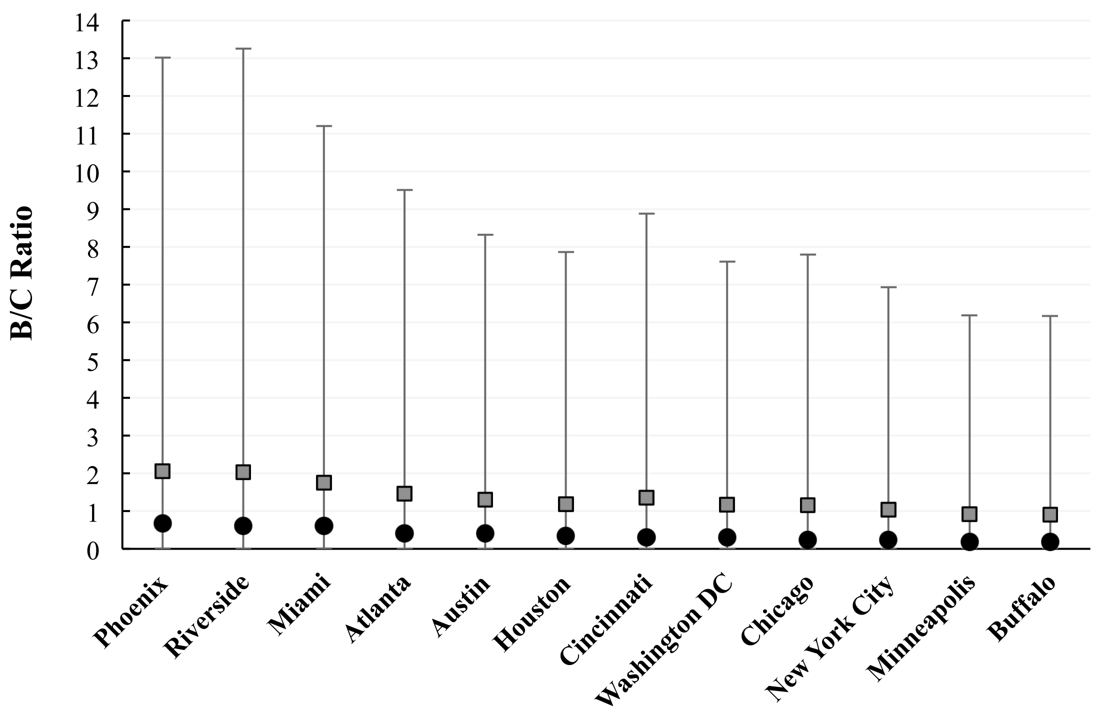

Figure 4. Benefit-to-cost ratios from using activated carbon filters in homes. The filled circle represents the median, the filled box represents the mean, and the whiskers represent the 95% confidence intervals of the distribution determined by the Monte Carlo simulation.

The upper bound of B/C ratios for each city ranged from approximately 6 to 13, indicating that some fraction of the population receives significant benefits from activated carbon filtration. This subset is generally characterized as a subpopulation with existing respiratory sensitivities (asthma, and other chronic pulmonary disorders), as well as the population over the age of 65, which generally has a much higher incidence rate for respiratory morbidity and mortality.

In order to explore strategies that significantly improve the impacts of carbon filtration in homes, the single pass removal efficiency for ozone was varied from 10% to 100% over the summer ozone season to determine what effect this parameter has on the B/C ratio in Phoenix. This range of single pass removal efficiencies is similar to experimental results for commercial carbon filters tested at 120 ppb of ozone by Lee and Davidson (1999). Figure 5 shows results of the model simulation. Even at 100% single pass removal efficiency, the median B/C ratio is less than 1.0 (0.92). However, the mean B/C ratio exceeds 1.0 with a single pass removal efficiency of 20% (1.39) and exceeds 2.0 with 40% single pass removal efficiency.

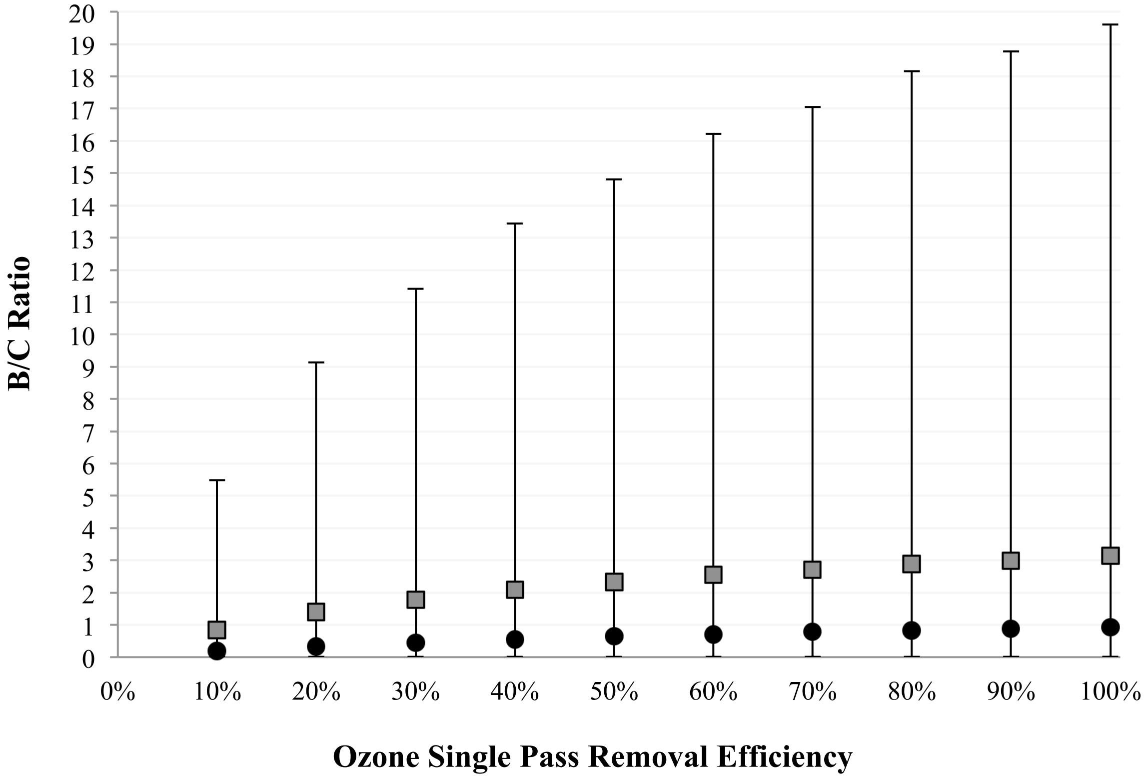

Figure 5. Benefit-to-cost ratios for homes in Phoenix, AZ. The filter efficiency is varied to show the B/C over multiple single pass removal efficiencies for ozone. The filled circle represents the median, the filled box represents the mean, and the whiskers represent the 95% confidence intervals of the distribution determined by the Monte Carlo simulation.

Fan operation at 100% increases the ozone removal effectiveness, but its impact on the benefit/cost ratio is not as obvious. As such, another simulation was conducted to estimate Ω and B/C ratios in Phoenix homes with 100% fan operation during the summer ozone season. Although ozone removal effectiveness was optimized (median Ω = 51%), the additional costs of 100% fan operation resulted in lower B/C ratios compared to using the standard HVAC cycling operation (median value of 0.68) due to increased energy costs.

Modeling the "Optimal" Home for Activated Carbon Filtration

A final set of residential analyses was completed to assess reasonable model parameters that lead to high B/C ratios. We assume that the "optimal" house for activated carbon filtration will be a home with high occupancy (at least four people per home), low surface reactivity (typical of homes with tile or wood floors versus carpet), 100% HVAC fan operation utilizing highly efficient electronically commutated motors to reduce additional energy costs (70% motor efficiency), and high performance filters with a single pass ozone removal efficiency of 90% or higher. Although not necessarily maximum values in a true optimization sense, these conditions are referred to here as "optimal". Simulation results are presented in Figure 6.

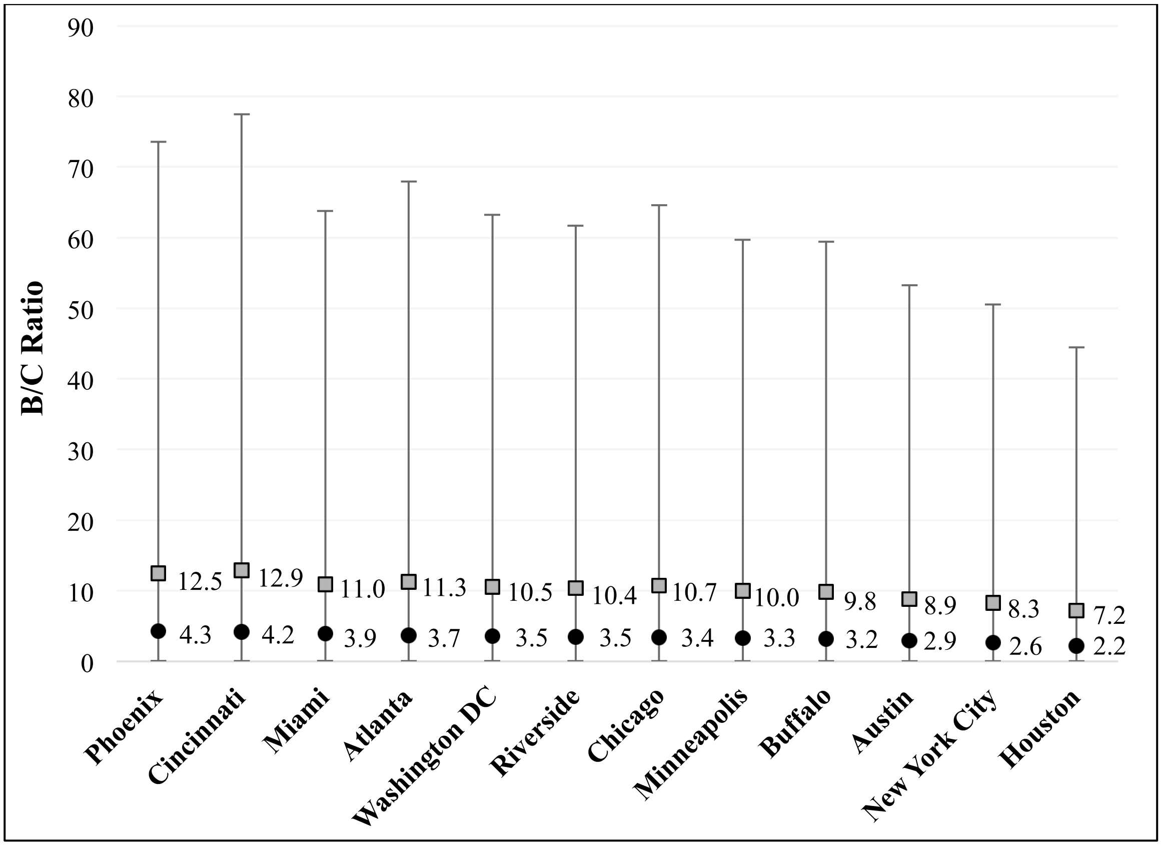

Figure 6. Benefit-to-cost ratios from using activated carbon filters in "optimal" homes. The filled circle represents the median, and the filled box represents the mean of the distribution. The whiskers represent the 95% confidence intervals of the Monte Carlo distribution.

As shown in Figure 6, all of the 12 cities have mean B/C values greater than 1.0 for the optimal condition. Phoenix, Cincinnati, and Miami all have median B/C values greater than 1.0. The benefits of activated carbon filtration in "optimal" homes are most directly associated with relatively high outdoor ozone concentrations, older population demographics, and lower local electricity costs. For example, the benefits in Austin and Houston are actually lower in comparison to standard conditions in those two cities, because both cities have relatively young populations. Finally, homes with more occupants will have higher benefits as more people are sharing the cost of carbon filtration.

Limitations of the Modeling Effort

Our analysis is conservative with regards to the scope of the health benefits achieved with carbon filtration, since reductions in secondary organic aerosols (SOAs) and other reaction products for which DALY parameters are unknown were not included in the health model. There is also very little research in the published literature regarding the performance of commercially available activated carbon filters in operational environments. This is a topic of research that should be investigated further.

Another limitation of this research is that we utilized long-term (i.e., seasonal) reductions in ozone exposure. Future research should investigate the changes in exposure in relationship to diurnal variations in outdoor ozone and dynamic HVAC cycling. These parameters should be investigated in parallel with occupancy in single-family homes to determine the true reductions in ozone exposure when using activated carbon filters.

Finally, the monetary benefits used in our analysis are conservative (i.e., much lower) in comparison to methods used by the USEPA to compare the costs and benefits of lowering ambient ozone standards. When considering the costs of carbon filtration in single-family homes, we deferred to using higher capital and operating costs when lacking sufficient data to estimate the true cost of filtration. In reality, the costs of carbon filtration may be lower, especially if filters are purchased in bulk and in homes with HVAC motor efficiencies greater than the standard conditions used in our analysis.

Conclusion

An integrated (systems) model was developed to estimate the benefits and costs of in-duct activated carbon control of ozone. The model can be used for any building scenario. An example application for single family homes in 12 U.S. cities was used here. When modeling carbon filtration in single-family homes across 12 cities in five different climate zones in the United States, the median indoor ozone removal effectiveness ranged from 4 to 20% during the summer ozone season. Due to the uncertainty of the mass balance and health analyses, a Monte Carlo simulation was used to estimate the potential benefits and costs of carbon filtration in single-family homes. For the parameters selected in this study, the mean predicted benefit/cost (B/C) ratios for 1-inch filters were greater than 1.0 in 10 of the 12 cities. However, the median benefit/cost ratios for all 12 cities were below 1.0, indicating a highly skewed B/C distribution. The highly skewed distribution is most directly attributed to the monetary benefits of reduced ozone-related health outcomes, especially in regards to what the average person is willing-to-pay for improved indoor air quality. Most importantly, the benefits of carbon filtration were optimized in homes with highly efficient HVAC systems, low ozone reactivity, high occupancy, and highly efficient carbon filters.
An important outcome of the modeling results described herein is the identification of areas for future research. Recommendations for future research include rigorous laboratory and field-testing of commercially available in-duct carbon filters for ozone removal efficiency and changes in efficiency over time. These filters are typically marketed for odor control, especially in residential applications. Little work has been

conducted to evaluate them for sustained ozone removal. Important metrics that should be measured over operational time include single-pass ozone removal efficiency, pressure drop and air flow rate (and incremental energy costs), and potential health effects. Finally, additional research should focus on how dynamic changes in outdoor ozone, HVAC cycling operation, and occupancy throughout the day impact exposures to ozone in single-family homes.

Benefit-Cost Analysis of Commercially Available Activated Carbon Filters for Indoor Ozone Removal in Residential Buildings

Supplemental Information

Equations S1 and S2 were assumed to be steady state in the model so that the $\partial C/\partial t$ term on the left hand side was assumed to equal zero. The mass balance parameters were then rearranged algebraically to develop Equation (1) in the main paper.

$$V\left(\frac{\partial C_{O3}}{\partial t}\right) = pQ_{inf}C_{o,O3} + \left(1 - f_{f,O3}\right)\left(1 - f_{c,O3}\right)H_{on}Q_{make-up}C_{o,O3} + \left(1 - f_{f,O3}\right)\left(1 - f_{c,O3}\right)H_{on}Q_{rec}C_{O3} + E_{O3} - Q_{exh}C_{O3} - H_{on}Q_{rec}C_{O3} - k^{*}_{dep,O3}C_{O3}V - \sum_j k_j C_j C_{O3}V \quad \textbf{(S1)}$$

Assuming a steady state and well mixed condition, Equation (S1) is further simplified:

$$C_{O3} = \frac{\{p\lambda_{inf}+(1-f_{f,O3})(1-f_{c,O3})H_{on}\lambda_{make-up}\}C_{o,O3}+ {E_{O3}}/{V}}{\lambda_{exh}+H_{on}\lambda_{rec}\{1-(1-f_{f,O3})(1-f_{c,O3})\}+ k^{*}_{dep,O3}+ \sum_j k_j C_j} \quad \textbf{(S2)}$$

Other assumptions for single-family homes include: no make-up ventilation, no ozone emission sources, a standard particle filter does not remove ozone (used for baseline indoor ozone concentration). It was also assumed that the exhaust rate in single-family homes would be primarily dominated by exfiltration, therefore $\lambda_{exh}= \lambda_{inf}$. Furthermore, the deposition of ozone to surfaces ($k_{dep,\,O3}^{*}$) will be dependent on whether the HVAC system is operating. Therefore, an averaging term was used to further simplify Equation (S2). The loss of ozone due to homogeneous reactions ($\sum_j k_j C_j$) was previously estimated using average indoor terpene concentrations and reaction constants (Corsi et al., 2014). The simplified mass balance for equation for ozone is presented in Equation (S3).

$$C_{O3} = \frac{p\lambda_{inf} C_{o,O3}}{\lambda_{inf} + H_{on}\lambda_{rec} f_{c,O3} + (H_{on} k^*_{dep,O3,AC_{on}} + (1 - H_{on}) k^*_{dep,O3,AC_{off}}) + \sum_j k_j C_j} \quad \textbf{(S3)}$$

Where,

λ_{inf}	=	Q_{inf}/V [hr^{-1}]
$\lambda_{make\text{-}up}$	=	$Q_{make\text{-}up}/V$ [hr^{-1}]
λ_{rec}	=	Q_{rec}/V [hr^{-1}]
λ_{exh}	=	Q_{exh}/V [hr^{-1}]
H_{on}	=	average annual fraction of time that the HVAC system operates [--]
C_{O3}	=	concentration of ozone in the occupied space [ppb, lbm•ft^{-3}]
$C_{o,O3}$	=	concentration of ozone in outdoor air [ppb, lbm•ft^{-3}]
C_j	=	concentration of gaseous reactant j in the occupied space [ppb, lbm•ft^{-3}]
E_{O3}	=	emission rate of ozone into occupied space [ppb•m^3•hr^{-1}, lbm•hr^{-1}]
$f_{c,O3}$	=	single-pass fractional removal of ozone by OACD [-]
$f_{f,O3}$	=	single-pass fractional removal of ozone by HVAC filter [-]
k_j	=	bimolecular homogeneous reaction rate constant [ppb^{-1}•hr^{-1}, lbm•ft^{-3}]
$k^*_{dep,O3}$	=	ozone decay rate for integrated background surfaces [hr^{-1}]
$k^*_{dep,O3,AC\_on}$	=	ozone decay rate for integrated background surfaces with HVAC on [h^{-1}]

$k^{*}_{dep,O3,\ AC\_off}$ = ozone decay rate for integrated background surfaces w/HVAC off [h^{-1}]

p = fractional penetration through the building envelope for ozone [-]

Q_{exh} = exhaust air volumetric flow rate [$m^3 \bullet hr^{-1}$, $ft^3 \bullet hr^{-1}$]

Q_{inf} = infiltration air volumetric flow rate [$m^3 \bullet hr^{-1}$, $ft^3 \bullet hr^{-1}$]

$Q_{make\text{-}up}$ = make-up (outdoor intake) air volumetric flow rate [$m^3 \bullet hr^{-1}$, $ft^3 \bullet hr^{-1}$]

Q_{rec} = recirculation air volumetric flow rate [$m^3 \bullet hr^{-1}$, $ft^3 \bullet hr^{-1}$]

V = volume of occupied space [m^3, ft^3]

Although reaction products were not used in the health functions of this analysis, the concentration of ozone reaction products in a single-family home can be determined by using Equations (S4) and (S5).

$$V(\partial C_{pi}/\partial t) = y_{si} v_{d,O3} A C_{O3} + \sum_j y_{ij} k_j C_j C_{O3} V \alpha_j + H_{on} Q_{rec}(1 - f_{f,pi})(1 - f_{c,pi}) C_{pi} + E_{pi,f} + E_{pi,c} - Q_{exh} C_{pi} - H_{on} Q_{rec} C_{pi} - v^{*}_{d,pi} A C_{pi} \quad \textbf{(S4)}$$

$$C_{pi} = \frac{y_{si} k^{*}_{dep,O3} C_{O3} + \sum_j y_{i,j} k_j C_j C_{O3} \alpha_j + {}^{E_{pi,f}}/_{V}}{\lambda_{exh} + H_{on} \lambda_{rec} \{1 - (1 - f_{f,pi})(1 - f_{c,pi})\} + k^{*}_{dep,pi}} \quad \textbf{(S5)}$$

Where,

λ_{rec} = Q_{rec}/V [hr^{-1}]

λ_{exh} = Q_{exh}/V [hr^{-1}]

α_j = conversion factor (ppb to $\mu g/m^3$) for reactant j (used only for SOA formation)

C_j = concentration of gaseous reactant j in the occupied space [ppb, $lbm \bullet ft^{-3}$]

C_{O3} = concentration of ozone in the occupied space [ppb, $lbm \bullet ft^{-3}$]

C_{pi} = concentration of ozone reaction product i in the occupied space [ppb, $lbm \bullet ft^{-3}$]

$E_{pi,c}$ = emission rate of product i due to formation in OACD [$ppb \bullet m^3 \bullet hr^{-1}$, $lbm \bullet hr^{-1}$]

$= y_{c,pi} H_{on} f_{c,pi} (1-f_{f,o3})(Q_{make\text{-}up} C_{o,o3} + Q_{rec} C_{o3})$

$E_{pi,f}$ = emission rate of product i from HVAC filter [ppb•m^3•hr^{-1}, lbm•hr^{-1}]
$= y_{f,pi} H_{on} f_{f,pi} (Q_{make\text{-}up} C_{o,o3} + Q_{rec} C_{o3})$

$f_{c,pi}$ = single-pass fractional removal of reaction product i by activated carbon filter [-]

$f_{f,pi}$ = single-pass fractional removal of reaction product i by standard HVAC filter [-]

H_{on} = average annual fraction of time that the HVAC system operates [--]

$k^*_{dep,O3}$ = ozone decay rate for integrated background surfaces [hr^{-1}]

$k^*_{dep,pi}$ = decay of reaction products to background surfaces [hr^{-1}]

k_j = bimolecular homogeneous reaction rate constant [ppb^{-1}•hr^{-1}, ft^3•lbm^{-1}•hr^{-1}]

$v^*_{d,pi}$ = deposition velocity of reaction product i to background surfaces [m•hr^{-1}, ft•hr^{-1}]

$y_{c,pi}$ = molar yield of product i from O_3 reaction with control device (moles i/moles O_3)

$y_{f,pi}$ = molar yield of product i from O_3 reaction with filter (moles i/moles O_3)

$y_{i,j}$ = molar (or mass for SOA) yield of product i from ozone reaction with j [($moles_i$/$moles_j$) for gas or (μg_i•m^{-3} / μg_j•m^{-3}; (lbm_i•ft^{-3} / lbm_j•ft^{-3}) for SOA]

y_{si} = molar (or mass for SOA) yield of product i from ozone reaction with background surfaces [($moles_i$/$moles_{O3}$) for gas or (μg_i•m^{-3} / μg_{O3}•m^{-3}; lbm_i•ft^{-3} / lbm_{O3}•ft^{-3} for SOA]

V = volume of occupied space [m^3, ft^3]

A box model showing the key model parameters is shown in Figure S.1.

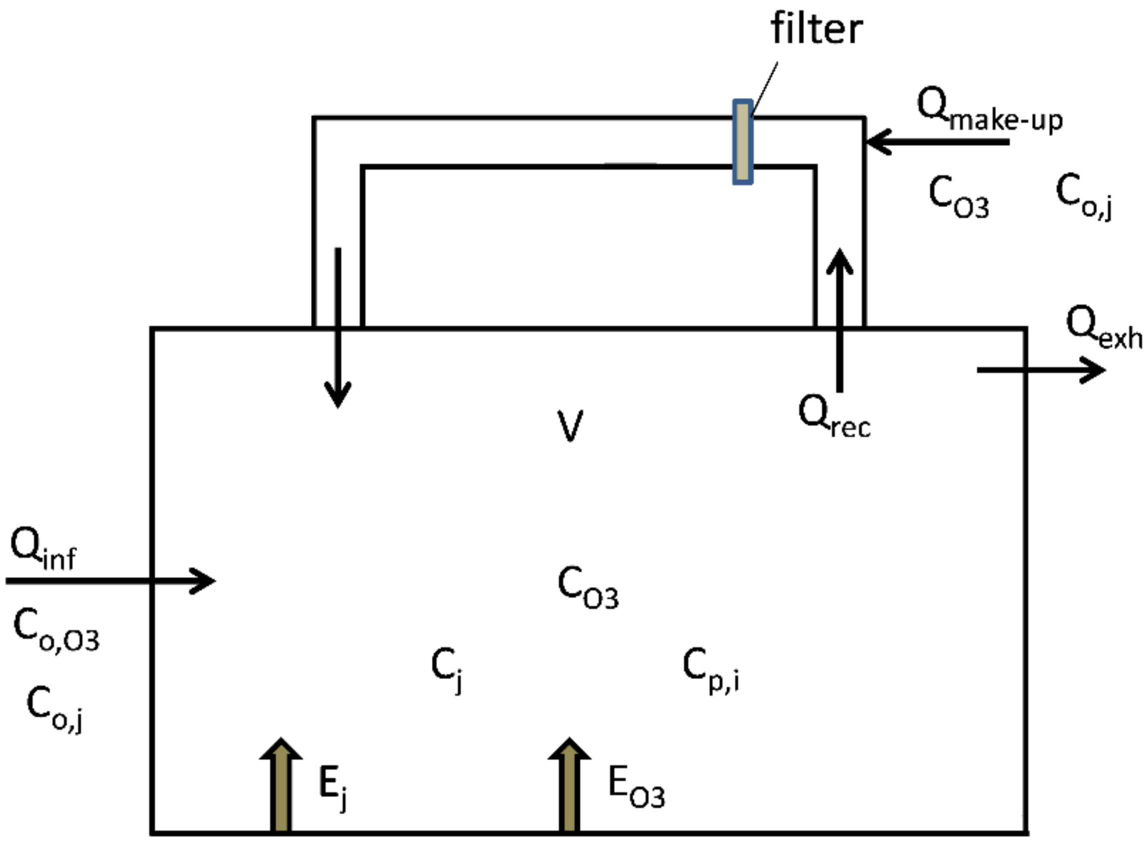

Figure S.1. Control volume for mass balance analyses.

Table S.1. Indoor terpene concentrations and ozone bi-molecular reaction rate constants.

Terpene	**Mean Residential Concentration (ppb)**	**Ozone Reaction Reaction Rate Constant (ppb^{-1}•hr^{-1})**
α-Pinene	2.70	0.0076
β-Pinene	0.59	0.0014
d-Limonene	3.63	0.0180
Styrene	0.35	0.0015
Linalool	0.23	0.0400
α-Terpineol	0.39	0.0270

Source: Corsi et al., (2014)

Table S.2. Metro population of sample cities with regional and climatic zone data.

City	Metro. Population	HDDs#	CDDs*	Climate Region (EIA)	Census Region	EPA Region	Sources
Atlanta	4,708,297	2,694	1,841	4	5	4	ASHRAE (2013) Chen et al. (2012) U.S. Census Bureau (2013)
Austin	1,412,271	1,654	2,989	5	7	6	
Buffalo	1,154,378	6,538	558	1	2	2	
Chicago	9,391,515	6,311	842	2	3	5	
Cincinnati	2,058,221	4,754	1,151	3	3	5	
Houston	5,180,443	1,414	3,001	5	7	6	
Miami	5,361,723	130	3,516	5	5	5	
Minneapolis	3,116,206	7,565	751	1	4	5	
New York	18,709,802	4,828	978	2	2	2	
Phoenix	3,715,360	941	4,557	5	8	9	
Riverside	3,793,081	1,622	1,550	4	9	9	
Wash. DC	5,139,549	4,735	1,119	3	9	9	
U.S.	309,300,000						

Heating Degree Days (HDDs), base temperature of 65 °F (18.3 °C)
* Cooling Degree Days (CDDs), base temperature of 65 °F (18.3 °C) (2009 ASHRAE Fundamentals)

Table S.3. Residential characteristic data for 12 U.S. cities.

City	Housing Units	Median House Size (ft^2)	Median Year of Construction	Survey Year	Median λ_{inf} (hr^{-1})
Atlanta	1,802,800	2,129	1985	2004	0.43
Austin	354,241[#]	1,956	n.d.[*]	2007	0.50
Buffalo	515,500	1,881	1948	2002	0.70
Chicago	3,198,900	2,017	1965	2003	0.61
Cincinnati	647,500	1,935	1962	1998	0.52
Houston	2,160,100	1,956	1980	2007	0.50
Miami	2,419,700	1,914	1978	2007	0.35
Minn.	1,329,700	2,157	1976	2007	0.60
New York	4,849,800	2,043	1951	2003	0.62
Phoenix	1,340,400	1,749	1983	2002	0.42
Riverside	1,511,800	1,735	1985	2002	0.42
Wash. DC	2,133,500	2,493	1974	2007	0.54
U.S.	155,108,000	1,700	1974	2011	0.44

[*]AHS had no data available for Austin—Houston housing data were used
[#]Austin housing stock only - does not include entire MSA
Chen et al. (2012)
U.S. Census Bureau (2013)
Persily et al. (2010)

Table S.4. Residential occupancy data for 12 U.S. cities.

City	Household Occupancy
Atlanta	2.18
Austin	2.37
Buffalo	2.24
Chicago	2.57
Cincinnati	2.17
Houston	2.67
Miami	2.58
Minneapolis	2.17
New York	2.61
Phoenix	2.64
Riverside	3.26
Washington DC	2.13

Source: U.S. Census Bureau (2013)

Persily et al. (2010) determined distributions of infiltration air exchange rates across single-family detached homes in nine geographic regions across the U.S (Table S.5). They assumed that the homes required conditioned air, the HVAC systems were balanced (i.e., supply flowrate equals exhaust flowrate), and that no make-up ventilation was used to bring fresh air into the home. They also assumed all system leaks (particularly from HVAC ducts) were contained within the conditioned space. Key parameters of their analysis include demographics, geography, climate, and the year of construction. Finally, the infiltration air exchange rate distributions from Persily et al. (2010) account for 80% of the U.S. residential building stock.

Table S.5. City-specific infiltration air exchange rates and distribution percentiles (hr^{-1}).

	Percentile										
City	**0**	**2.5**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**97.5**	**100**
Atlanta	0.00	0.07	0.12	0.19	0.33	0.49	0.65	0.80	0.89	0.97	1.74
Austin	0.00	0.05	0.09	0.15	0.28	0.44	0.60	0.75	0.84	0.91	1.59
Buffalo	0.00	0.04	0.08	0.13	0.27	0.44	0.62	0.80	0.90	0.99	1.67
Chicago	0.00	0.04	0.08	0.14	0.27	0.46	0.65	0.84	0.95	1.04	1.83
Cincinnati	0.00	0.04	0.08	0.14	0.27	0.45	0.65	0.83	0.94	1.04	1.69
Houston	0.00	0.05	0.09	0.15	0.28	0.44	0.60	0.75	0.84	0.92	1.43
Miami	0.00	0.07	0.12	0.19	0.33	0.49	0.65	0.80	0.89	0.98	1.56
Minneapolis	0.00	0.04	0.08	0.15	0.29	0.49	0.70	0.89	1.01	1.11	1.85
New York City	0.00	0.04	0.08	0.13	0.27	0.44	0.62	0.79	0.90	0.99	1.63
Phoenix	0.00	0.10	0.15	0.22	0.35	0.51	0.66	0.80	0.88	0.95	1.44
Riverside	0.00	0.06	0.10	0.16	0.27	0.41	0.55	0.67	0.75	0.81	1.25
Washington	0.00	0.07	0.12	0.19	0.33	0.49	0.65	0.81	0.90	0.97	1.59

Source: Persily et al. (2010)

City-specific HVAC cycling rate fractions were determined from previous work compiled by Lawrence Berkeley National Laboratories (LBNL) (Table S.6). The data compiled by LBNL estimated the total number of hours that a typical residential air conditioning (AC) unit would operate during the summer cooling season. The median cycling fraction for each city was calculated by dividing the total number of AC operation hours by the total number of hours from 1 May to 30 September (3,672). The probabilistic distribution of the AC cycling rate was unknown, so we assumed a uniform distribution. We also assumed that the minimum and maximum values were 10% lower and higher (respectively) than the median value.

Table S.6. City-specific HVAC cycling rate fractions and distribution percentiles during the summer cooling season (1 May to 31 September).

	Percentile										
City	**0**	**2.5**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**97.5**	**100**
Atlanta	0.11	0.11	0.12	0.13	0.16	0.21	0.26	0.29	0.30	0.31	0.31
Austin	0.20	0.21	0.21	0.22	0.25	0.30	0.35	0.38	0.39	0.39	0.40
Buffalo	0.00	0.00	0.01	0.01	0.03	0.06	0.10	0.12	0.12	0.13	0.13
Chicago	0.00	0.00	0.01	0.02	0.04	0.09	0.13	0.15	0.16	0.17	0.17
Cincinnati	0.01	0.01	0.02	0.03	0.06	0.11	0.16	0.19	0.20	0.21	0.21
Houston	0.20	0.20	0.21	0.22	0.25	0.30	0.35	0.38	0.39	0.40	0.40
Miami	0.28	0.28	0.29	0.30	0.33	0.38	0.43	0.46	0.47	0.48	0.48
Minneapolis	0.00	0.00	0.01	0.02	0.04	0.09	0.13	0.15	0.16	0.17	0.17
New York City	0.00	0.01	0.01	0.02	0.05	0.10	0.15	0.18	0.19	0.20	0.20
Phoenix	0.27	0.28	0.28	0.29	0.32	0.37	0.42	0.45	0.46	0.46	0.47
Riverside	0.09	0.09	0.10	0.11	0.14	0.19	0.24	0.27	0.28	0.28	0.29
Washington	0.02	0.02	0.03	0.04	0.07	0.12	0.17	0.20	0.21	0.21	0.22

Source: LBNL (2014)

Table S.7. Electricity costs per kWh for each of the target cities and end-use.

City	Residential $/kWh	Commercial $/kWh
Atlanta	0.11	0.10
Austin	0.11	0.08
Buffalo	0.18	0.15
Chicago	0.11	0.08
Cincinnati	0.11	0.09
Houston	0.11	0.08
Miami	0.11	0.10
Minneapolis	0.11	0.09
New York City	0.18	0.15
Phoenix	0.11	0.10
Riverside	0.16	0.13
Washington DC	0.12	0.12

Source: USEIA (2014)

Table S.8. 8-hour ozone attainment classification and population in nonattainment.

City	8-Hour Ozone Design Value (ppb)	Attainment Classification	Population in Nonattainment Counties	Regional Ozone Trend (2000-2012)	Sources
Atlanta	80	Marginal	4,753,017	-17%	
Austin		Attainment		0%	
Buffalo		Attainment		-7%	
Chicago	77	Marginal	9,179,738	-5%	
Cincinnati	79	Marginal	1,988,951	-5%	USEPA (2013a)
Houston	84	Marginal	5,891,999	0%	USEPA (2013b)
Miami		Attainment		-17%	
Minn.		Attainment		4%	
NYC	84	Marginal	20,217,137	-7%	
Phoenix	77	Marginal	3,849,627	-4%	
Riverside	95	Severe 15	425,806	-9%	
Wash. DC	81	Marginal	5,136,216	-17%	
U.S. Population in Nonattainment			**51,442,491**	**National Avg (-9%)**	

Table S.9. City-specific summer ozone concentrations from 2011 through 2013.

City	USEPA Ozone Monitor	Ozone Season(s)	# Obs	Min. (ppb)	Median (ppb)	Mode (ppb)	Max. (ppb)	Mean (ppb)	Std. Dev. (ppb)
Atlanta	013-121-0055	2011-2013	10864	2	28	2	114	31	21
		2013	3624	2	24	2	114	26	18
		2012	3616	2	30	2	114	33	21
		2011	3624	2	33	2	99	35	22
Austin	048-453-0014	2011-2013	10213	2	31	13	105	33	17
		2013	3624	2	29	13	85	31	16
		2012	3429	2	31	30	105	32	16
		2011	3160	2	34	38	88	35	18
Buffalo	036-029-0002	2011-2013	10706	2	34	2	95	35	17
		2013	3458	2	34	2	86	34	16
		2012	3624	2	37	2	95	37	18
		2011	3624	2	32	28	81	33	15
Chicago	017-031-0064	2011-2013	10680	2	30	2	139	31	17
		2013	3458	2	28	2	73	28	13
		2012	3598	2	34	2	110	35	18
		2011	3624	2	30	2	139	31	17
Cincinnati	039-061-0006	2011-2013	10732	2	34	2	112	36	19
		2013	3624	2	32	29	83	33	16
		2012	3511	2	35	2	109	38	20
		2011	3597	2	35	2	112	37	21
Houston	048-201-1035	2011-2013	10668	2	20	2	131	23	18
		2013	3448	2	19	2	89	22	16
		2012	3609	2	19	2	131	23	18
		2011	3611	2	22	2	122	25	19
Miami	012-086-0027	2011-2013	10187	2	25	22	101	27	10
		2013	3368	2	24	22	101	25	9
		2012	3510	2	26	25	77	27	9
		2011	3309	2	26	22	88	28	11
Minn.	027-139-0505	2011-2013	10825	2	32	2	102	32	15
		2013	3577	2	34	28	83	34	15
		2012	3624	2	33	2	102	33	16
		2011	3624	2	29	2	82	28	13
NYC	036-061-0135	2011-2013	10423	2	26	2	121	28	16
		2013	3624	2	25	2	94	26	14
		2012	3624	2	28	2	97	30	17
		2011	3175	2	26	2	121	29	18
Phoenix	004-013-3003	2011-2013	10872	2	39	43	98	39	19
		2013	3624	2	39	46	98	38	18
		2012	3624	2	39	38	96	40	19
		2011	3624	2	39	2	95	39	20
Riverside	06-065-0012	2011-2013	8797	2	46	41	127	47	21
		2013	2469	2	46	45	115	47	19
		2012	2704	2	48	41	117	49	21
		2011	3624	2	44	2	127	44	21
Wash.	011-001-0041	2011-2013	10724	2	32	2	102	33	18
		2013	3624	2	29	2	90	29	15
		2012	3559	2	35	2	102	36	18
		2011	3541	2	33	2	101	33	19

Source: USEPA (2014a)

Table S.10. Difference in indoor ozone concentrations in single-family homes with and without activated carbon filtration.

	mean (μ)	std dev (σ)	Percentile										
			0	**2.5**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**97.5**	**100**
Atlanta	0.53	0.65	0.00	0.02	0.04	0.07	0.15	0.33	0.66	1.18	1.65	2.19	25.7
Austin	0.58	0.67	0.00	0.03	0.05	0.08	0.18	0.38	0.73	1.27	1.75	2.30	19.0
Buffalo	0.24	0.40	0.00	0.00	0.01	0.01	0.04	0.12	0.28	0.57	0.88	1.25	11.0
Chicago	0.26	0.41	0.00	0.00	0.01	0.01	0.05	0.13	0.31	0.64	0.95	1.32	10.4
Cincinnati	0.36	0.53	0.00	0.01	0.02	0.03	0.08	0.20	0.44	0.86	1.25	1.74	17.4
Houston	0.45	0.56	0.00	0.02	0.03	0.06	0.13	0.29	0.57	1.02	1.42	1.89	22.4
Miami	0.55	0.57	0.00	0.04	0.07	0.11	0.21	0.39	0.70	1.16	1.56	2.03	14.4
Minn.	0.28	0.42	0.00	0.00	0.01	0.02	0.05	0.14	0.33	0.66	0.97	1.37	9.34
NYC	0.26	0.41	0.00	0.00	0.01	0.02	0.05	0.13	0.31	0.63	0.94	1.31	12.1
Phoenix	0.82	0.88	0.00	0.06	0.09	0.15	0.29	0.57	1.04	1.75	2.37	3.10	21.9
Riverside	0.61	0.74	0.00	0.03	0.05	0.09	0.19	0.39	0.76	1.35	1.90	2.55	18.5
Wash. DC	0.37	0.51	0.00	0.01	0.02	0.04	0.09	0.21	0.46	0.86	1.25	1.71	13.0

Table S.11. Population age fractions by metropolitan area.

City	Population Age Fractions									
	1 to 4	5 to 14	15 to 24	25 to 34	35 to 44	45 to 54	55 to 64	65 to 74	75 to 84	85+
Atlanta	0.06	0.10	0.17	0.19	0.15	0.13	0.10	0.05	0.03	0.01
Austin	0.07	0.12	0.17	0.21	0.15	0.12	0.09	0.04	0.02	0.01
Buffalo	0.07	0.13	0.18	0.15	0.12	0.14	0.11	0.06	0.04	0.02
Chicago	0.07	0.12	0.15	0.19	0.14	0.13	0.10	0.06	0.03	0.02
Cincinnati	0.07	0.12	0.17	0.17	0.12	0.14	0.11	0.05	0.04	0.02
Houston	0.08	0.15	0.15	0.18	0.16	0.12	0.07	0.05	0.03	0.01
Miami	0.06	0.12	0.14	0.14	0.15	0.15	0.11	0.07	0.05	0.02
Minn.	0.06	0.12	0.18	0.21	0.16	0.12	0.06	0.04	0.03	0.02
New York	0.06	0.12	0.14	0.17	0.14	0.14	0.11	0.06	0.04	0.02
Phoenix	0.08	0.16	0.15	0.16	0.15	0.13	0.09	0.05	0.03	0.01
Riverside	0.08	0.18	0.17	0.15	0.16	0.12	0.06	0.05	0.03	0.01
Wash DC	0.06	0.09	0.17	0.20	0.14	0.13	0.11	0.06	0.04	0.02

Source: U.S. Census Bureau (2012)

The average indoor ozone concentrations from Table S.10 were scaled by 70% (this assumes that the average person spends 70% of their time in their home) and entered into the health and benefits model as described in the main text. The health model incorporates city-specific age populations (Table S.11) for baseline incidence, change in health incidence, and change in DALYs. The results of the analysis for each of the sample cities are presented in Tables S.12 through S.23.

Table S.12 Population adjusted ozone health outcomes for Atlanta single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
19400	Mortality (25 to 34)	0.00	0.03	0.87	(0.29, 1.44)
15000	Mortality (35 to 44)	0.00	0.04	1.10	(0.37, 1.83)
12500	Mortality (45 to 54)	0.00	0.09	1.94	(0.66, 3.22)
9500	Mortality (55 to 64)	0.01	0.14	2.56	(0.87, 4.25)
5400	Mortality (65 to 74)	0.02	0.18	2.39	(0.81, 3.97)
2900	Mortality (75 to 84)	0.05	0.24	2.31	(0.78, 3.83)
1400	Mortality (85+)	0.13	0.30	1.63	(0.55, 2.70)
46700	Respiratory HA (18 to 64)	0.01	0.17	0.01	(0.00, 0.01)
46700	Dysrhythmia HA (18 to 64)	0.00	0.03	0.00	(0.00, 0.00)
9700	Dysrhythmia HA (65+)	0.13	0.92	0.03	(0.00, 0.06)
46700	MRAD (18 to 64)	7.80	536	0.25	(0.10, 0.39)
18800	School Loss Day (5 to 17)	9.90	1042	0.73	(0.28, 1.18)
9700	Respiratory HA (65+)	0.04	0.32	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.13. Population adjusted ozone health outcomes for Austin single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
20900	Mortality (25 to 34)	0.00	0.04	1.02	(0.35, 1.70)
15000	Mortality (35 to 44)	0.00	0.05	1.20	(0.41, 2.00)
12100	Mortality (45 to 54)	0.00	0.09	2.05	(0.69, 3.41)
8800	Mortality (55 to 64)	0.01	0.14	2.59	(0.88, 4.30)
3800	Mortality (65 to 74)	0.02	0.14	1.84	(0.62, 3.05)
2200	Mortality (75 to 84)	0.05	0.20	1.91	(0.65, 3.18)
1000	Mortality (85+)	0.13	0.23	1.27	(0.43, 2.11)
46350	Respiratory HA (18 to 64)	0.00	0.18	0.01	(0.00, 0.01)
46350	Dysrhythmia HA (18 to 64)	0.00	0.03	0.00	(0.00, 0.00)
7000	Dysrhythmia HA (65+)	0.13	0.73	0.02	(0.00, 0.04)
46350	MRAD (18 to 64)	7.80	582	0.27	(0.11, 0.43)
20350	School Loss Day (5 to 17)	9.90	1232	0.86	(0.33,1.39)
7000	Respiratory HA (65+)	0.04	0.26	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.14. Population adjusted ozone health outcomes for Buffalo single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
14500	Mortality (25 to 34)	0.00	0.01	0.30	(0.10, 0.49)
12000	Mortality (35 to 44)	0.00	0.02	0.40	(0.14, 0.67)
14000	Mortality (45 to 54)	0.00	0.04	0.99	(0.34, 1.65)
10800	Mortality (55 to 64)	0.01	0.07	1.33	(0.45, 2.21)
5900	Mortality (65 to 74)	0.02	0.09	1.19	(0.40, 1.98)
4300	Mortality (75 to 84)	0.05	0.16	1.57	(0.53, 2.60)
1500	Mortality (85+)	0.13	0.15	0.80	(0.27, 1.33)
44050	Respiratory HA (18 to 64)	0.01	0.08	0.00	(0.00, 0.00)
44050	Dysrhythmia HA (18 to 64)	0.00	0.01	0.00	(0.00, 0.00)
11700	Dysrhythmia HA (65+)	0.13	0.52	0.02	(0.00, 0.03)
44050	MRAD (18 to 64)	7.80	231	0.11	(0.04, 0.17)
21800	School Loss Day (5 to 17)	9.90	554	0.39	(0.15, 0.63)
11700	Respiratory HA (65+)	0.04	0.18	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.15. Population adjusted ozone health outcomes for Chicago single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
18800	Mortality (25 to 34)	0.00	0.02	0.42	(0.14, 0.70)
14100	Mortality (35 to 44)	0.00	0.02	0.52	(0.17, 0.86)
12700	Mortality (45 to 54)	0.00	0.04	0.98	(0.33, 1.63)
9700	Mortality (55 to 64)	0.01	0.07	1.30	(0.44, 2.17)
5600	Mortality (65 to 74)	0.02	0.09	1.24	(0.42, 2.05)
3400	Mortality (75 to 84)	0.05	0.14	1.35	(0.46, 2.24)
1600	Mortality (85+)	0.13	0.17	0.93	(0.31, 1.54)
45900	Respiratory HA (18 to 64)	0.01	0.09	0.00	(0.00, 0.00)
45900	Dysrhythmia HA (18 to 64)	0.00	0.01	0.00	(0.00, 0.00)
10600	Dysrhythmia HA (65+)	0.13	0.51	0.02	(0.00, 0.03)
45900	MRAD (18 to 64)	7.80	263	0.12	(0.05, 0.19)
19850	School Loss Day (5 to 17)	9.90	550	0.39	(0.15, 0.62)
10600	Respiratory HA (65+)	0.04	0.18	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.16. Population adjusted ozone health outcomes for Cincinnati single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
16600	Mortality (25 to 34)	0.00	0.02	0.51	(0.17, 0.85)
11900	Mortality (35 to 44)	0.00	0.02	0.60	(0.20, 1.00)
13700	Mortality (45 to 54)	0.00	0.07	1.47	(0.50, 2.44)
10600	Mortality (55 to 64)	0.01	0.11	1.97	(0.67, 3.27)
5400	Mortality (65 to 74)	0.02	0.12	1.65	(0.56, 2.74)
3800	Mortality (75 to 84)	0.05	0.22	2.09	(0.71, 3.47)
2000	Mortality (85+)	0.13	0.29	1.61	(0.54, 2.67)
44500	Respiratory HA (18 to 64)	0.01	0.12	0.00	(0.00, 0.01)
44500	Dysrhythmia HA (18 to 64)	0.00	0.02	0.00	(0.00, 0.00)
11200	Dysrhythmia HA (65+)	0.14	0.78	0.02	(0.00, 0.05)
44500	MRAD (18 to 64)	7.80	353	0.16	(0.07, 0.26)
20150	School Loss Day (5 to 17)	9.90	772	0.54	(0.21, 0.87)
11200	Respiratory HA (65+)	0.05	0.27	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.17. Population adjusted ozone health outcomes for Houston single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000	
		y_0		mean (μ)	95% CIs
18000	Mortality (25 to 34)	0.00	0.03	0.69	(0.23, 1.15)
16100	Mortality (35 to 44)	0.00	0.04	1.02	(0.34, 1.69)
12000	Mortality (45 to 54)	0.00	0.07	1.60	(0.54, 2.67)
6900	Mortality (55 to 64)	0.01	0.09	1.60	(0.54, 2.66)
4700	Mortality (65 to 74)	0.02	0.13	1.79	(0.61, 2.98)
2800	Mortality (75 to 84)	0.05	0.20	1.92	(0.65, 3.19)
900	Mortality (85+)	0.13	0.17	0.90	(0.31, 1.50)
44000	Respiratory HA (18 to 64)	0.00	0.13	0.00	(0.00, 0.01)
44000	Dysrhythmia HA (18 to 64)	0.00	0.02	0.00	(0.00, 0.00)
8400	Dysrhythmia HA (65+)	0.13	0.67	0.02	(0.00, 0.04)
44000	MRAD (18 to 64)	7.80	435	0.20	(0.08, 0.32)
22750	School Loss Day (5 to 17)	9.90	1087	0.76	(0.29, 1.23)
8400	Respiratory HA (65+)	0.04	0.23	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.18. Population adjusted ozone health outcomes for Miami single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
13700	Mortality (25 to 34)	0.00	0.02	0.64	(0.22, 1.06)
15100	Mortality (35 to 44)	0.00	0.05	1.16	(0.39, 1.92)
14500	Mortality (45 to 54)	0.00	0.10	2.35	(0.79, 3.90)
10700	Mortality (55 to 64)	0.01	0.16	3.01	(1.02, 5.00)
7400	Mortality (65 to 74)	0.02	0.26	3.42	(1.16, 5.68)
4700	Mortality (75 to 84)	0.05	0.40	3.90	(1.32, 6.48)
1900	Mortality (85+)	0.13	0.42	2.31	(0.78, 3.83)
47150	Respiratory HA (18 to 64)	0.01	0.20	0.01	(0.00, 0.01)
47150	Dysrhythmia HA (18 to 64)	0.00	0.03	0.00	(0.00, 0.00)
14000	Dysrhythmia HA (65+)	0.13	1.40	0.04	(0.00, 0.08)
47150	MRAD (18 to 64)	7.80	565	0.26	(0.11, 0.41)
18850	School Loss Day (5 to 17)	9.90	1090	0.76	(0.29, 1.23)
14000	Respiratory HA (65+)	0.04	0.49	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.19. Population adjusted ozone health outcomes for Minneapolis single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
20600	Mortality (25 to 34)	0.00	0.02	0.48	(0.16, 0.80)
16400	Mortality (35 to 44)	0.00	0.03	0.63	(0.21, 1.05)
11800	Mortality (45 to 54)	0.00	0.04	0.96	(0.32, 1.59)
5900	Mortality (55 to 64)	0.01	0.04	0.83	(0.28, 1.38)
4000	Mortality (65 to 74)	0.02	0.07	0.92	(0.31, 1.54)
3300	Mortality (75 to 84)	0.05	0.14	1.37	(0.46, 2.28)
1700	Mortality (85+)	0.13	0.19	1.03	(0.35, 1.72)
44400	Respiratory HA (18 to 64)	0.00	0.08	0.00	(0.00, 0.00)
44400	Dysrhythmia HA (18 to 64)	0.00	0.01	0.00	(0.00, 0.00)
9000	Dysrhythmia HA (65+)	0.14	0.48	0.01	(0.00, 0.03)
44400	MRAD (18 to 64)	7.80	266	0.12	(0.05, 0.20)
21200	School Loss Day (5 to 17)	9.90	615	0.43	(0.16, 0.70)
9000	Respiratory HA (65+)	0.05	0.17	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.20. Population adjusted ozone health outcomes for New York City single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
17000	Mortality (25 to 34)	0.00	0.01	0.38	(0.13, 0.63)
14400	Mortality (35 to 44)	0.00	0.02	0.53	(0.18, 0.88)
13500	Mortality (45 to 54)	0.00	0.05	1.04	(0.35, 1.73)
10700	Mortality (55 to 64)	0.01	0.08	1.44	(0.49, 2.39)
6400	Mortality (65 to 74)	0.02	0.11	1.41	(0.48, 2.34)
4000	Mortality (75 to 84)	0.05	0.16	1.59	(0.54, 2.64)
1700	Mortality (85+)	0.13	0.18	0.99	(0.33, 1.64)
44400	Respiratory HA (18 to 64)	0.01	0.09	0.00	(0.00, 0.00)
44400	Dysrhythmia HA (18 to 64)	0.00	0.02	0.00	(0.00, 0.00)
12100	Dysrhythmia HA (65+)	0.13	0.58	0.02	(0.00, 0.03)
44400	MRAD (18 to 64)	7.80	269	0.12	(0.05, 0.20)
18600	School Loss Day (5 to 17)	9.90	515	0.36	(0.14, 0.58)
12100	Respiratory HA (65+)	0.04	0.20	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.21. Population adjusted ozone health outcomes for Phoenix single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000	
		y_0		mean (μ)	95% CIs
15900	Mortality (25 to 34)	0.00	0.04	1.11	(0.37, 1.84)
14500	Mortality (35 to 44)	0.00	0.07	1.66	(0.56, 2.75)
13300	Mortality (45 to 54)	0.00	0.14	3.21	(1.09, 5.33)
9400	Mortality (55 to 64)	0.01	0.21	3.94	(1.33, 6.55)
4600	Mortality (65 to 74)	0.02	0.24	3.17	(1.07, 5.26)
2600	Mortality (75 to 84)	0.05	0.33	3.22	(1.09, 5.35)
1000	Mortality (85+)	0.13	0.33	1.81	(0.61, 3.01)
45150	Respiratory HA (18 to 64)	0.01	0.27	0.01	(0.00, 0.01)
45150	Dysrhythmia HA (18 to 64)	0.00	0.04	0.00	(0.00, 0.00)
8200	Dysrhythmia HA (65+)	0.13	1.19	0.04	(0.00, 0.07)
45150	MRAD (18 to 64)	7.80	807	0.37	(0.15, 0.59)
23000	School Loss Day (5 to 17)	9.90	1981	1.39	(0.53, 2.24)
8200	Respiratory HA (65+)	0.04	0.42	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.22. Population adjusted ozone health outcomes for Riverside single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
14500	Mortality (25 to 34)	0.00	0.03	0.75	(0.26, 1.25)
15800	Mortality (35 to 44)	0.00	0.05	1.35	(0.46, 2.24)
11700	Mortality (45 to 54)	0.00	0.09	2.11	(0.71, 3.51)
6400	Mortality (55 to 64)	0.01	0.11	2.00	(0.68, 3.33)
4600	Mortality (65 to 74)	0.02	0.18	2.37	(0.80, 3.93)
3200	Mortality (75 to 84)	0.05	0.31	2.96	(1.00, 4.92)
1000	Mortality (85+)	0.13	0.25	1.35	(0.46, 2.25)
41150	Respiratory HA (18 to 64)	0.00	0.17	0.01	(0.00, 0.01)
41150	Dysrhythmia HA (18 to 64)	0.00	0.02	0.00	(0.00, 0.00)
8800	Dysrhythmia HA (65+)	0.13	0.97	0.03	(0.00, 0.06)
41150	MRAD (18 to 64)	7.80	549	0.25	(0.11, 0.40)
26200	School Loss Day (5 to 17)	9.90	1688	1.18	(0.45, 1.91)
8800	Respiratory HA (65+)	0.04	0.34	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

Table S.23. Population adjusted ozone health outcomes for Washington single-family homes.

Affected Population (out of 100,000 persons)	Health Outcome	Baseline Incidence per person y_0	Δ *Incidence* per 100,000	Δ *DALYs* per 100,000 mean (μ)	95% CIs
20100	Mortality (25 to 34)	0.00	0.02	0.64	(0.22, 1.06)
13700	Mortality (35 to 44)	0.00	0.03	0.71	(0.24, 1.19)
12700	Mortality (45 to 54)	0.00	0.06	1.40	(0.47, 2.32)
10700	Mortality (55 to 64)	0.01	0.11	2.04	(0.69, 3.40)
6100	Mortality (65 to 74)	0.02	0.14	1.91	(0.65, 3.18)
3600	Mortality (75 to 84)	0.05	0.21	2.03	(0.69, 3.38)
1700	Mortality (85+)	0.13	0.26	1.40	(0.47, 2.33)
41150	Respiratory HA (18 to 64)	0.01	0.13	0.00	(0.00, 0.01)
41150	Dysrhythmia HA (18 to 64)	0.00	0.02	0.00	(0.00, 0.00)
11400	Dysrhythmia HA (65+)	0.13	0.78	0.02	(0.00, 0.05)
41150	MRAD (18 to 64)	7.80	384	0.18	(0.07, 0.28)
17300	School Loss Day (5 to 17)	9.90	681	0.48	(0.18, 0.77)
11400	Respiratory HA (65+)	0.04	0.27	0.00	(0.00, 0.00)

Sources: U.S. Census Bureau (2012); USEPA (2012)

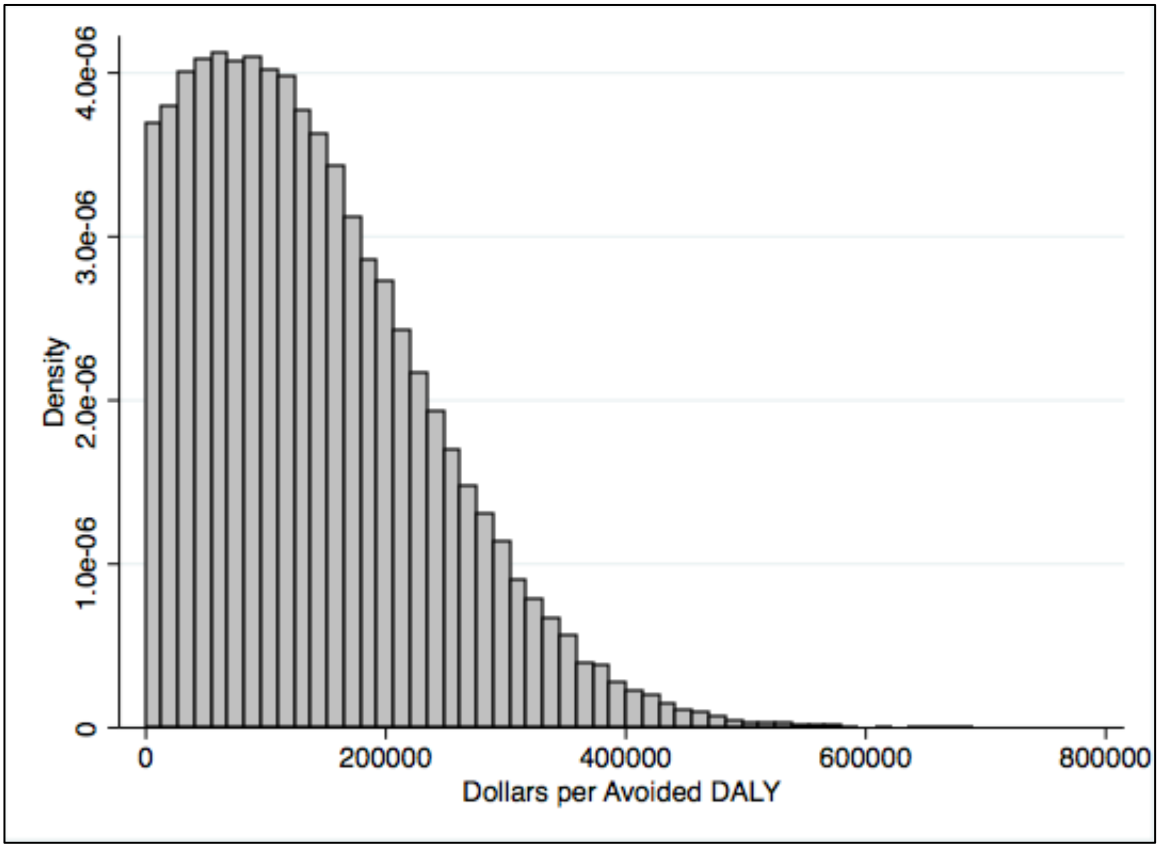

Figure S.2. Histogram of predicted willingness-to-pay values per avoided DALY.

Table S.24. Willingness-to-pay per avoided DALY distribution percentiles (-).

Percentile										
0	**2.5**	**5**	**10**	**25**	**50**	**75**	**90**	**95**	**97.5**	**100**
$0	$6,940	$13,600	$26,810	$63,920	$125,590	$201,710	$277,800	$324,630	$366,020	$691,050

Source: Bobinac et al. (2014)

A sensitivity analysis of the systems model was conducted to determine which modeling parameters had the most impact on the final results. The sensitivity analysis included parameters that affect the transport of ozone from outdoors to indoors, building and HVAC operational conditions, indoor ozone chemistry, cost inputs for ozone control via activated carbon filtration, and benefit inputs for disability-adjusted life-years (DALYs). A base case condition was defined for each model parameter for single-family homes. Reasonable minimum and maximum values on either sides of the base case were selected for each parameter.

In order to test the sensitivity against the base case, each parameter was tested using the minimum and maximum values for that parameter while all other parameters were held constant at their respective base case values. As each parameter was tested, the ozone removal effectiveness and the benefit/cost ratio (B/C) were determined. Estimated base case parameters are presented in S.25 below (Corsi et al., 2014). The sensitivity analysis results for ozone removal effectiveness and B/C ratios are presented in Figures S3 and S4, respectively.

Table S.25. Parameter values for residential sensitivity analysis.

Variable	Min	Base Case	Max
Outdoor ozone (ppb) (annual average)	10	30	60
Ozone penetration factor (--)	0.66	0.79	0.92
Volume (m^3)	225	500	1500
λ_{inf} (hr^{-1})	0.1	0.5	1.5
$Q_{make-up}$ ($m^3 \bullet hr^{-1}$)	0	0	78
$Q_{recirculation}$ ($m^3 \bullet hr^{-1}$)	2500	2800	3100
Particle filter efficiency for removal of ozone (%)	0	10%	20%
AcC filter efficiency (%)	20%	70%	90%
Ozone decay rate (hr^{-1})	1.0	4.0	8.5
α-Pinene concentration (ppb)	0.42	2.64	40.89
α-Pinene ozone rxn rate constant ($ppb^{-1} \bullet hr^{-1}$)	0.0073	0.0085	0.0292
β-Pinene concentration (ppb)	0.17	0.60	13.02
β Pinene ozone rxn rate constant ($ppb^{-1} \bullet hr^{-1}$)	0.0011	0.0012	0.0013
d-Limonene concentration (ppb)	0.46	3.17	12.03
d-Limonene ozone rxn rate constant ($ppb^{-1} \bullet hr^{-1}$)	0.0176	0.0203	0.0575
Styrene concentration (ppb)	0.01	0.32	2.70
Styrene ozone rxn rate constant ($ppb^{-1} \bullet hr^{-1}$)	0.00075	0.0015	0.003
Linalool concentration (ppb)	0.03	2.47	21.16
Linalool ozone rxn rate constant ($ppb^{-1} \bullet hr^{-1}$)	0.0396	0.0464	0.0531
α-Terpeniol concentration (ppb)	0.055	0.11	0.22
α-Terpeniol ozone rxn rate constant ($ppb^{-1} \bullet hr^{-1}$)	0.01	0.027	0.05
Time in environment (%)	35%	70%	100%
Average occupancy (--)	1.00	2.59	6.00
Filter replacement frequency per year (--)	1	2	4
Annual average HVAC usage (%)	1%	20%	50%
Average HVAC system efficiency (%)	12.5%	25%	50%
Difference in filter costs for 1" filter ($)[a]	$0	$5	$15
Difference in filter costs for 2" filter ($)[a]	$0	$10	$20
Difference in filter costs for 4" filter ($)[a]	$0	$15	$25
Cost per kWh ($)	$0.07	$0.12	$0.33
Cost per DALY ($)	$42,000	$150,000	$220,000

a = difference in filter costs between a particle combination filter and a standard particle filter.

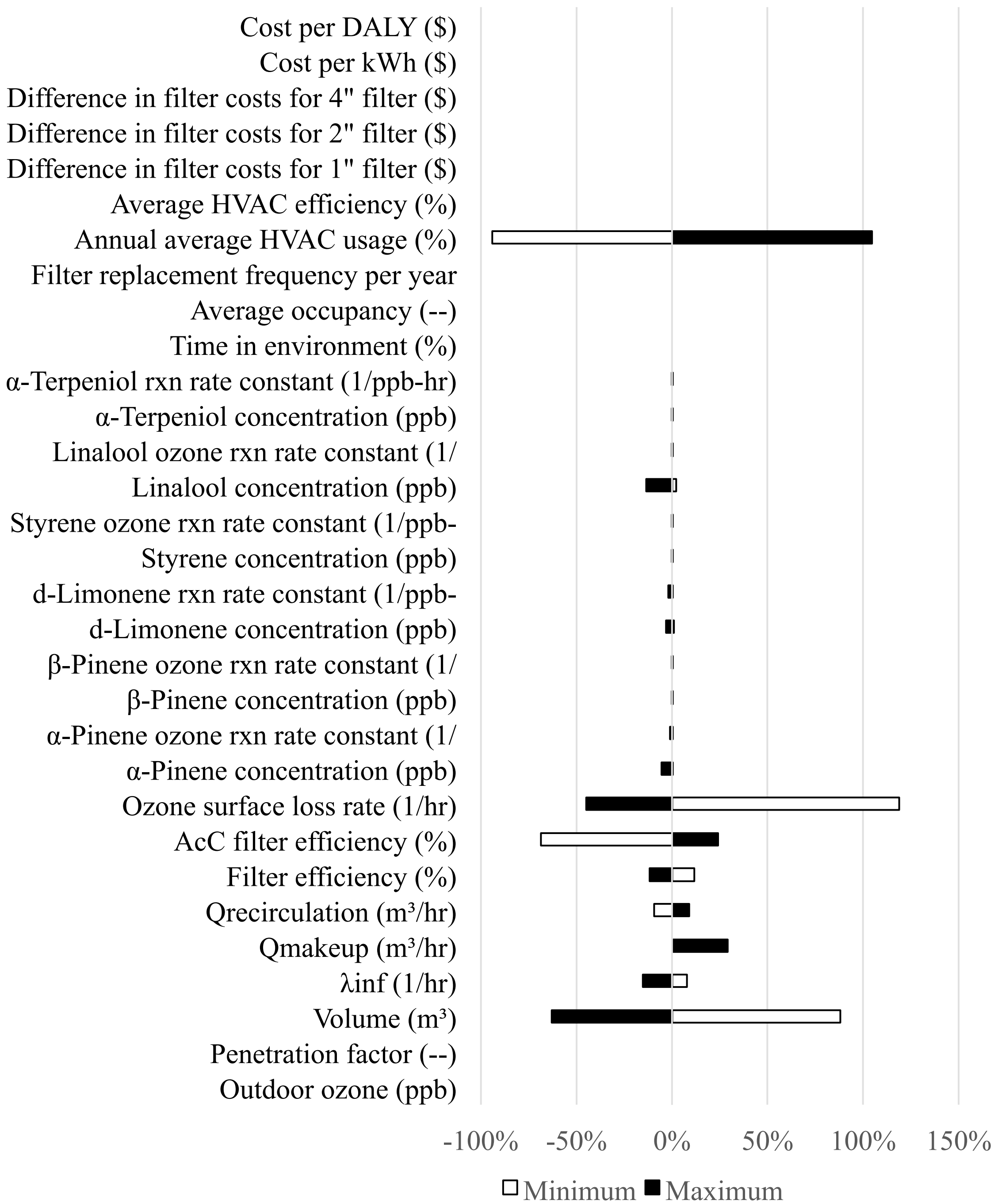

Figure S.3. Sensitivity of ozone removal effectiveness to variations in model parameters for residential buildings equipped with activated carbon filters (base case, minimum, and maximum parameter values are listed in Table S.25).

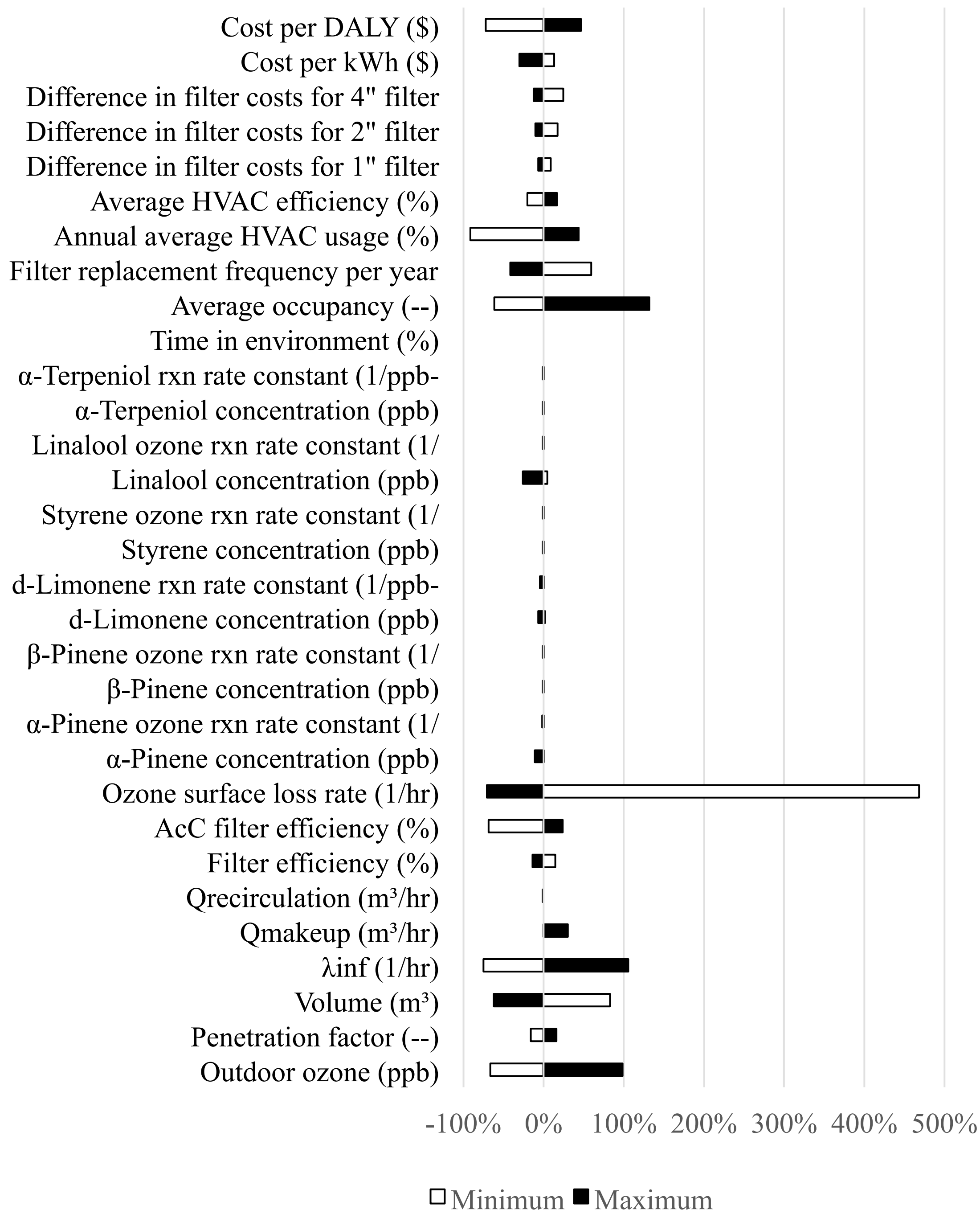

Figure S.4. Sensitivity of benefit/cost ratio to variations in model parameters for residential buildings equipped with activated carbon filters (base case, minimum, and maximum parameter values are listed in Table S.25).

The base case ozone removal effectiveness for residential buildings was 13%. The annual HVAC operational frequency, building volume, and ozone decay rate have the greatest impacts on ozone removal effectiveness in residential buildings (Figures S.3). As expected, filter and electricity costs dominate the overall cost (Figure S.4). Occupancy is also important because having more people per residence reduces the individual costs and increases the health benefits, which are shared by more people.

The removal effectiveness of combination activated carbon (AcC) filters for each target pollutant in residential buildings is higher in residences with low surface loss rates for ozone (ozone decay rates), e.g., little floor coverage with carpet, and relatively high HVAC usage. Changes in residential B/C ratios for AcC filtration are primarily dominated by parameters associated with the filter, including filter costs, electricity costs, and replacement frequency. Ozone deposition to surfaces is also important, as lower deposition rates result in a higher benefit associated with activated carbon filtration. Finally, AcC filters provide significant benefits when ambient ozone is high, indicating potential for applications only during the summer ozone season.

Pressure drop curves were also developed for standard particle filters based on information compiled from product brochures and from filter test data. The increase in pressure drop across carbon filters was estimated by subtracting pressure drops across carbon filters from those for standard particle filters with the same particle removal rating. The resulting incremental (differences in) pressure drop curves are shown in Figure S.5. The additional pressure drops shown in Figure S.5 are used to determine the incremental change in energy costs of using combination filters. The pressure drop relationships used for this analysis were based on new filters, primarily due to a lack of data available to develop relationships for used filters for a spectrum of operational conditions. It was assumed here that particle and AcC filters are equally loaded with particles and the corresponding difference in the two pressure drops remain constant during filter lifetimes.

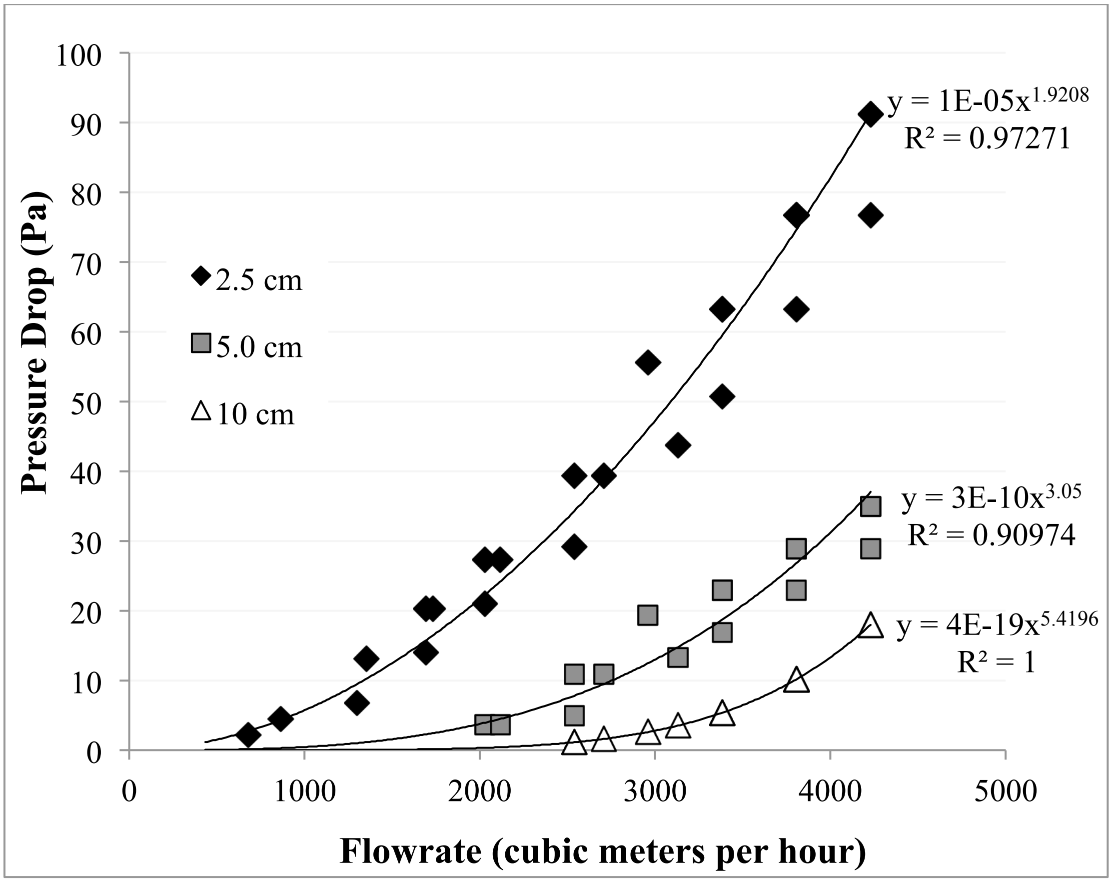

Figure S.5. Estimated differences in pressure drop between a standard particle filter and a combination activated carbon and particle filter for 2.5 cm (1-inch), 5.0 cm (2-inch), and 10 cm (4-inch) deep filters.

A final modeling simulation incorporated an assumption that all of the ozone-related health outcomes would apply only during the summer ozone season. In the previous analyses, the calculated DALYs were scaled by 5/12 in order to compare the benefits with the associated filter energy costs from 1 May to 30 September. However, in other analyses that incorporate USEPA protocols for determining health outcomes from ozone exposure, the health outcomes for the entire year were assumed to occur during the ozone season (1 May to 30 September). Berman et al. (2012) and Hubbell et al. (2005) used USEPA modeling software to evaluate the potential health benefits of reductions in ambient ozone from 1 May to 30 September in cities across the U.S. The USEPA regulatory impact assessment for ozone (USEPA, 2014b) incorporates health outcome functions that were originally applied to the summer ozone season, and some of the applied ozone controls (e.g., regulating gasoline vapor pressure) are only used during the summer season. When removing the scaling factor in our model, the median B/C for Phoenix approaches 1.0 when using a carbon filter with a single pass removal efficiency for ozone of approximately 45% as shown in Figure S.6. The ASHRAE minimum standard efficiency for ozone control is 40% (ASHRAE, 2013), which implies that commercially available carbon filters may be economically viable for ozone removal in homes, especially for individuals sensitive to ozone. Monetary benefits versus filter efficiency for this analysis are presented in Figure S.7.

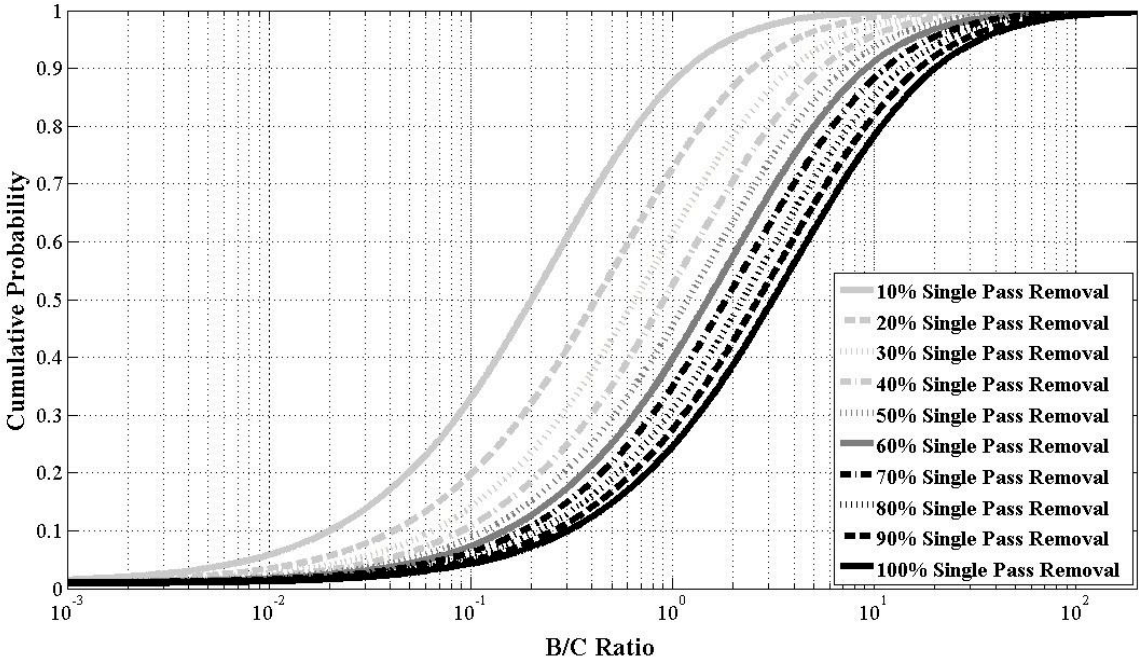

Figure S.6. Benefit-to-cost ratios from using activated carbon filters in homes in Phoenix, AZ assuming all ozone-related health outcomes occur only during the ozone season from 1 May to 30 September. The filter efficiency is varied to show the B/C over multiple single pass removal efficiencies for ozone.

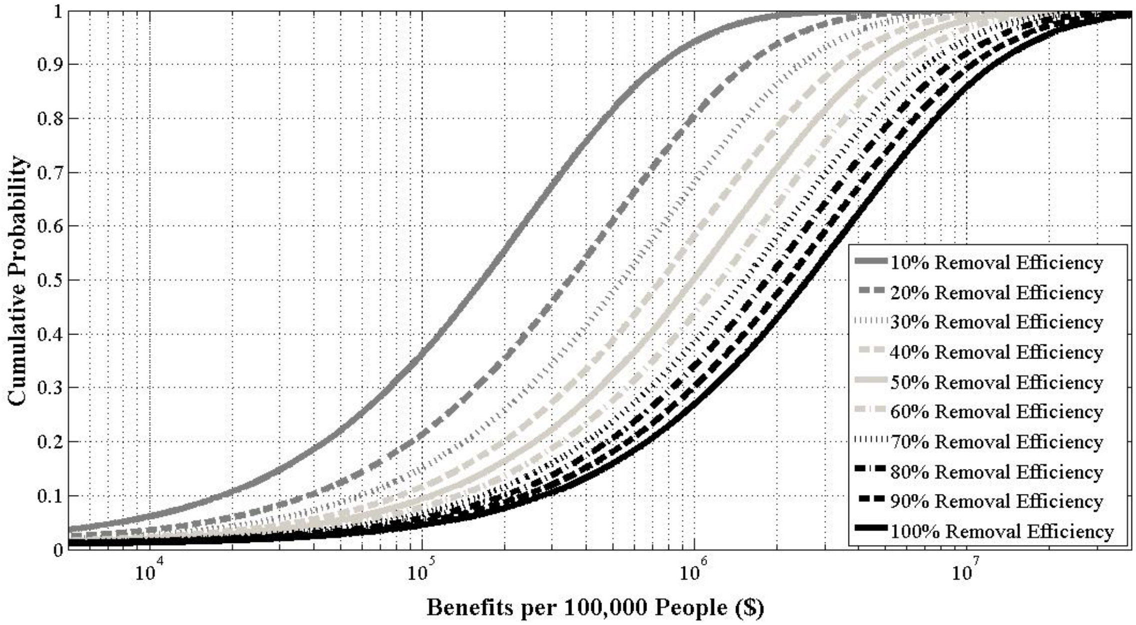

Figure S.7. Monetary benefits from using activated carbon filters in homes in Phoenix, AZ assuming all ozone-related health outcomes occur only during the ozone season from 1 May to 30 September. The filter efficiency is varied to show the B/C over multiple single pass removal efficiencies for ozone.

Appendix B

PAPER II

Cost-Benefit Analysis of Commercially Available Activated Carbon Filters for Indoor Ozone Removal in Buildings

(Submitted to *Science and Technology for the Built Environment*)

Abstract

This study involved the development of a model for evaluating the potential costs and benefits of ozone control by activated carbon filtration in buildings. The modeling effort included the prediction of indoor ozone and ozone reaction products with and without activated carbon filtration in the HVAC system. As one application, the model was used to predict benefit-to-cost ratios for various types of buildings in 12 American cities in five different climate zones. Health benefits were evaluated using the disability-adjusted life-years attributed to the difference in indoor ozone concentration with and without activated carbon filtration and included city-specific age demographics for each simulation. Costs of commercially available activated-carbon filters included capital cost differences when compared to conventional HVAC filters of similar MERV rating, energy penalties due to additional pressure drop, and regional utility rates. When assuming a single pass ozone removal efficiency of 60%, carbon filtration during the ozone season was beneficial and economically viable in commercial office buildings, long-term healthcare facilities, and K-12 schools. Additionally, benefits for residential filtration were marginal in most cities, but could be highly beneficial for those with respiratory illness. Finally, residential filtration could be economically viable for

conditions of higher ozone removal efficiencies, lower filter costs, and lower pressure drop across the filter.

Key Words

Chemistry, control, commercial buildings, disability-adjusted life-years, benefit-cost analysis, modeling.

Practical Applications

Ozone and ozone reaction products have been linked to increased incidences of mortality and morbidity. Approximately 50% of ozone exposure occurs indoor. As such, effective ozone control via carbon filtration can provide health benefits, especially in cities with high ambient ozone concentrations during the summer ozone season.

Introduction

Tropospheric ozone is formed due to chemical reactions involving nitrogen oxides (NO_x) and volatile organic compounds (VOCs) in the presence of sunlight. Despite an average decrease in ozone concentrations in the U.S. by 28% since 1980, nearly 1/3 of Americans still live and work in counties with ozone concentrations that exceed the primary eight-hour average National Ambient Air Quality Standard (NAAQS) for ozone (USEPA, 2013). Exposure to ozone has been linked to premature mortality (Bell et al., 2005; Ito et al., 2005; Jerrett et al., 2009; Levy et al., 2005; Smith et al., 2009; USEPA, 2006, and references provided therein), increases in respiratory-related hospital admissions (e.g., Burnett et al., 1999), minor restricted activity days (e.g., Ostro and Rothschild, 1989), and school loss days (e.g., Chen et al., 2000). As such, there have been increasing efforts to develop new methods to reduce ozone concentrations, including reducing ozone precursors (USEPA, 2014) and recommending ozone filtration in buildings located in regions with high seasonal ozone concentrations (ASHRAE, 2013a).

Nearly half of personal ozone exposure in the United States occurs in indoor environments (Weschler, 2006). Indoor ozone concentrations are generally 30-70% of outdoor ozone concentrations (Weschler, 2000), with much lower percentages in newer homes with tight construction and air conditioning (Chen et al., 2012; Smith et al., 2009). Furthermore, exposures to indoor ozone have recently been linked to premature mortality (Chen et al., 2012).

While indoor ozone can be harmful in its own right, it can also react with compounds commonly found indoors to create harmful by-products, many of which have generally higher concentrations indoors than outdoors (Weschler, 2006). More specifically, ozone can react with material surfaces (heterogeneous reactions) that include *carpet* (Wang and Morrison, 2010; Coleman et al., 2008; Wang and Morrison, 2006; Morrison and Nazaroff, 2002), *paint* (Cros et al., 2012; Lamble et al., 2011; Reiss et al., 1995), and *ceiling tile* (Cros et al., 2012; Lamble et al., 2011) to form C1-C12 carbonyls. Additionally, ozone will react with unsaturated organic compounds (homogenous reactions) such as *α-pinene*, *β-pinene*, *d-limonene*, *linalool*, and *styrene,* all of which are common in indoor environments (Youssefi and Waring 2012; Logue et al., 2011; Chen and Hopke, 2010; Chen and Hopke, 2009; Lee et al., 2006; Nazaroff et al., 2006; Ng et al., 2006; Leungsakul et al., 2005; Nazaroff and Weschler, 2004; Atkinson and Arey, 2003; Fan et al., 2003; Grosjean and Grosjean, 1997; Grosjean and Grosjean, 1996; Weschler and Shields, 1996; Grosjean et al., 1993).

Ozone-alkene reaction products include irritating and potentially toxic compounds such as formaldehyde and acetaldehyde (Weschler, 2006), as well as secondary organic aerosols (SOA) (Chen and Hopke, 2010; Chen and Hopke, 2009; Sarwar and Corsi, 2007; Fan et al., 2003; Sarwar et al., 2003). Neither the acute nor chronic health effects of exposure to indoor SOA are well understood.

Activated carbon filters have been shown to be effective at removing ozone in buildings (Ginestet et al., 2013; Fisk, 2009; Gundel et al., 2002; Shields et al., 1999) and may be an economically viable method to improve health in the indoor environment. This will be especially true in buildings with a large proportion of make-up ventilation air, such as office buildings, health facilities, and schools. The consequences of using commercially available activated carbon filters can include an increased filter cost compared to standard filters, potentially higher pressure drop across the filter (and a higher electricity cost), and longevity of the filter. All of these factors need to be fully investigated to determine the health benefits and costs of ozone exposure in buildings.

Model Development

The overall objective of this study was to complete an assessment of the benefit-to-cost ratio (B/C) associated with commercially available activated carbon filters in HVAC systems. To accomplish this objective a systems model consisting of interconnected components was developed (Figure 1). The model is referred to as CO3B-Calc.

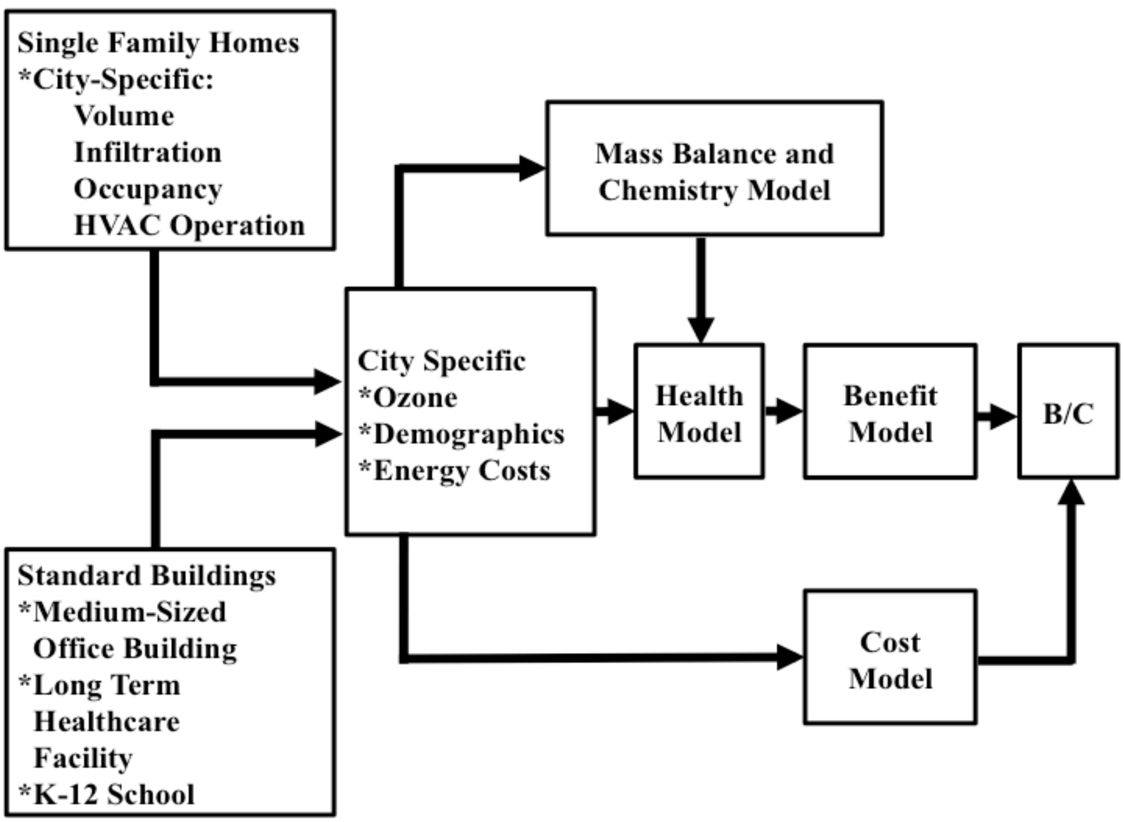

Figure 1. Conceptual model illustrating interconnected sub models of CO3B-Calc model.

The integrated systems model was previously described in detail by Aldred et al. (2015) and Corsi et al. (2014). Primary metrics of the model include ozone removal effectiveness and benefit-to-cost ratio. Ozone removal effectiveness is defined as the percent reduction in indoor ozone concentration when an ozone control device is used relative to an identical condition when such a device is not used, as described by Equation (1).

$$\Omega = (1 - C_{AcC}/C_{No\_AcC}) * 100\% \qquad \textbf{(1)}$$

Where,
Ω = ozone removal effectiveness of activated carbon filter (%)
C_{AcC} = indoor ozone concentration with activated carbon filter installed (ppb)
C_{No_AcC} = indoor ozone concentration without activated carbon filter installed (ppb)

The concentrations of ozone and reaction products with and without carbon filtration are determined from steady-state (time-averaged) mass balance equations. Based on available health response models (Logue et al., 2012; Huijbregts et al., 2005), only formaldehyde and acetaldehyde were considered as reaction products in this study.

The health model uses concentration-response functions and city-specific demographics to determine changes in health incidence due to ozone and reaction product exposures in accordance with USEPA protocols (USEPA, 2012). The changes in health incidence are then converted to disability-adjusted life-years (DALYs). A difference in DALYs (or ΔDALYs) is then determined by subtracting the DALYs due to ozone and reaction product exposures with carbon filtration from the baseline (no carbon filter) condition. Finally, the monetary benefits are determined by summing the health benefits ($\sum \Delta$DALYs) and multiplying by a dollar value per DALY, which was estimated as \$150,000 per avoided DALY (Bobinac et al., 2014).

The costs of activated carbon filtration are determined by summing all of the filtration cost parameters, which include replacement frequency, additional energy costs, and additional labor costs. The resulting benefit-to-cost ratio (B/C) is determined as shown in Equation (2).

$$B/C = \left((\textstyle\sum_{i=1}^{n} \Delta DALYs) * f\right)/(n_f(\Delta x_F + \Delta x_E + \Delta x_L)) \qquad \textbf{(2)}$$

Where,

B/C	= benefit-to-cost ratio (-)
$(\sum_{i=1}^{n} \Delta DALYs)$	= sum of DALYs for all health outcomes due to ozone exposure (DALYs)
f	= monetary value per DALY (\$150,000/DALY)
n_f	= number of carbon filters in the filter bank (-)
Δx_F	= difference in cost between standard particle filter and carbon filter (\$)
Δx_E	= difference in energy costs between particle and carbon filter (\$)
Δx_L	= difference in labor costs between particle and carbon filter (\$)

Modeling the Effects of Climate, Geography, and Demographics

The modeling analysis focused on the baseline conditions in 12 cities across the United States. At least two cities from each of the five climate zones defined by the Energy Information Administration were selected for the analysis (USEIA, 2013). Climate zones are defined by number of heating degree-days and cooling degree-days. The cities selected for this analysis include: Atlanta, Austin, Buffalo, Chicago, Cincinnati, Houston, Miami, Minneapolis, New York City, Phoenix, Riverside, and Washington D.C. This sample of cities accounts for a broad nationwide sample of population, climate, building stock, and ambient ozone concentrations. In addition, city-specific parameters such as the average occupancy of single-family homes, population age fractions, and regional energy costs were also accounted for in the integrated systems model. Single-family homes were modeled using city-specific housing parameters to determine the ozone removal effectiveness and B/C ratio of activated carbon filtration. Commercial buildings, including office buildings, long term healthcare facilities, and K-12 schools were modeled using standardized building parameters and city-specific ozone, demographics, and energy costs.

Modeling Methods for Single-Family Homes

City-specific data sourced from public records and the published literature were used to model single-family homes in the 12 sample cities (Aldred et al., 2015; Corsi et al., 2014; LBNL, 2014; USEPA, 2014; USEIA, 2013; USCB, 2012; Stephens et al., 2011; Persily et al., 2010; Lee et al., 1999). The potential benefits from the use of activated carbon filters include health outcomes for all age groups. For this analysis, only 2-inch filters were considered for the benefit-cost analysis, and it was assumed that two filters would be required during the summer ozone season (1 May to 30 September) to maintain a minimum single pass ozone removal efficiency of 60%. Additional modeling assumptions are presented in Table 1.

Modeling Methods for Commercial Office Building

Mechanical system usage in commercial buildings is governed by the ventilation requirements of the building. ASHRAE Standard 62.1 (ASHRAE, 2013a) and the purpose of the building dictate ventilation (i.e., make-up air) requirements. Additional ventilation air is brought into the building when an air side economizer is used. In this case, ozone removal by a carbon filter could be much higher as more outdoor air is cycled through the filter (versus recirculated air).

The U.S. Department of Energy and ASHRAE have developed commercial prototype building models (USDOE, 2012) for various types of commercial buildings in accordance with ASHRAE Standard 90.1 (ASHRAE, 2013b). The commercial building prototypes for small, medium, and large commercial buildings were used in the city-specific commercial building analysis. Results for medium-sized commercial building are highlighted in this study.

The integrated systems model focuses on health benefits achieved during the peak ozone season (1 May – 30 September), and it was assumed for this analysis that the HVAC system is operational 100% while the building is occupied to meet the ventilation requirements for office buildings. To calculate the energy costs associated with carbon filtration, it was assumed that the building is occupied during normal working hours (8 hours per day, 5 days per week) and that the HVAC system is operational 11 hours per day and 5 days per week. It was also assumed that the maximum face velocity of air entering the carbon filters is 2 m/s, which is equivalent to 2,000 cubic feet per minute (cfm) for a filter with a face area of 24” x 24” (61cm x 61cm). The number of filters in the filter bank was determined by the maximum flow rate and by assuming 25% make-up air. Electricity costs were assumed to be constant, as opposed to demand costs. The error in this assumption is likely small given that the majorities of the costs for a 2-inch carbon filter are attributed to capital and labor costs. Other key modeling assumptions are presented in Table 1.

Table 1. Key parameter values used for modeling of each building type.

Modeling Parameter	Units	Single Family Home	Medium-Sized Commercial Office Building	Long-Term Healthcare Facility	K-12 School
Occupancy	People	City-Specific	269	30	1,433
Volume	m^3	City-Specific	15,000	1,500	27,226
Infiltration[1]	hr^{-1}	City-Specific	0.2	0.2	0.2
HVAC Operation When Occupied	%	City-Specific	100	100	100
Time In Occupied Environment	%	70	20	90	20
Ozone Penetration Factor[2]	-	0.8	0.8	0.8	0.8
Single Pass Removal Efficiency	%	60	60	60	60
Ventilation Requirement[3]	$m^3 \bullet hr^{-1}$	0	8,337	3,000	42,600
Recirculation Air Exchange Rate[4]	hr^{-1}	7.6	4	4	6.3
Ozone Decay Rate (HVAC Off)[5]	hr^{-1}	2.8	2.8	2.8	2.8
Ozone Decay Rate (HVAC On)[6]	hr^{-1}	5.4	4	4	4
Number of Filters / Season	#	2	2	2	2
Number of Filters / System	#	1	10	4	19
Δ Filter Costs[7]	$	14.72	14.72	14.72	14.72
Labor and Disposal (per filter)	$	0	17	17	17
Health Outcomes	Ages	0-100	18-64	65-100	5-17
α-Pinene Concentration	ppb[*]	2.70	0.55	0.55	0.24
β-Pinene Concentration	ppb	0.59	0.01	0.01	0.00
d-Limonene Concentration	ppb	3.63	1.65	1.65	0.79
Linalool Concentration	ppb	0.23	0.00	0.00	0.00
Styrene Concentration	ppb	0.35	0.21	0.21	0.01

1. Infiltration is the air-exchange infiltration rate due to penetration of outdoor air through the building envelope.
2. Ozone penetration factor is the fraction of outdoor ozone that penetrates through the building envelope.
3. The ventilation (or make-up air) requirement is dictated by occupational use and ASHRAE Standard 62.1-2013.
4. The recirculation rate is equal to the flowrate of recirculated air divided by the volume of the conditioned space.
5. The ozone decay rate with the HVAC off is a measurement of ozone decay to indoor surfaces with the HVAC off.
6. The ozone decay rate with the HVAC on is a measurement of ozone decay to indoor surfaces with the HVAC on.
7. This is the median price differential for activated carbon filters, a range of values was provided by a filter retailer.

* ppb = parts per billion

Modeling Methods for Long Term Healthcare Facilities

Long-term healthcare facilities were modelled as light commercial buildings (volume of 1,500 m^3) with 30 occupants, all over the age of 65. Ventilation standards were based on guidance provided in ASHRAE Standard 170 for healthcare facilities (ASHRAE, 2008). It was assumed that occupants, i.e., patients, were inside the building 90% of the time. The cost model also included HVAC characteristics typically observed in light commercial buildings (Azimi and Stephens, 2013). Health benefits were modelled using health incidence functions for persons over the age of 65 years (USEPA, 2012); health care workers were not considered in the DALY analysis. Building operation and health benefits were only considered for the summer ozone season (1 May to 30 September). Age-specific baseline incidence and health parameters are provided in detail in Aldred et al. (2015) and Corsi et al. (2014). Additional modeling assumptions are presented in Table 1.

Modeling Methods for K-12 Schools

School facilities were modelled as medium-sized commercial buildings (volume of 27,226 m^3) with 1,433 occupants using the ASHRAE Standard 90.1 Prototype Building for a primary school (USDOE, 2012). Ventilation standards were based on guidance provided in ASHRAE Standard 62.1 (ASHRAE, 2013a) for elementary educational facilities. It was assumed that students are in school buildings 20% of the year, and that the HVAC system is operational 31% of the year (similar to the commercial building model). The number of filters (19) was determined by assuming a constant face velocity of 2 m/s, a filter face area of 24" x 24" (61cm x 61cm), and make-up ventilation required by Standard 62.1. The fraction of make-up air in supply air was assumed to be 25% (42,600 $m^3 \cdot hr^{-1}$).

Health functions for children between the ages of five and 17 were used for the benefit analysis; teachers and other school staff were not considered in the analysis. Building operation and health benefits were only considered for the summer ozone season (1 May to 30 September). For the benefits model, the value per school loss day used by Hubbell et al. (2005) was adjusted for inflation ($105 in 2014 USD) (U.S. Bureau of Labor Statistics, 2014). This value incorporates time lost at work by a parent staying home with a child during the school absence and does not include the direct costs to the school district, as this cost varies by district and state.

A conversion factor of 1.5 was used to convert average daily ozone to 8-hour daily ozone per guidance provided in USEPA (2012) and the baseline incidence of school loss days was assumed to be 9.9 per year per child (Hubbell et al., 2005). It was assumed that every preventable school absence resulted in 1.6 school loss days and an adjustment factor of 0.393 was used to estimate exposure in schools during the summer ozone season (i.e., 39.3% of the school year occurs during the ozone season from 1 May to 30 September) (USEPA, 2012).

Modeling Uncertainty

The greatest uncertainty of the results lies in the health functions of the integrated systems model. In order to accurately capture the uncertainty in the health outcomes, error propagation was used to determine the mean and 95% confidence intervals of the calculated DALYs (Spadaro and Rabl, 2008; Burmaster and Hull, 1997; Slob, 1994). Lognormal functions, specifically the health functions for formaldehyde and acetaldehyde, were normalized when comparing with normal health functions.

Results and Discussion

The ozone removal effectiveness for in-duct carbon filtration varies by city and by building type as shown in a sample of cities presented in Figure 2. Removal effectiveness varies considerably when evaluating single-family homes, as HVAC cycling rates vary based on cooling demand. Conversely, values of removal effectiveness are nearly equivalent from city to city for the three other building types, as HVAC operation is dictated by ventilation requirements for the building type. This is most evident when evaluating the removal effectiveness in K-12 schools, since schools require a much higher proportion of ventilation air than commercial office buildings.

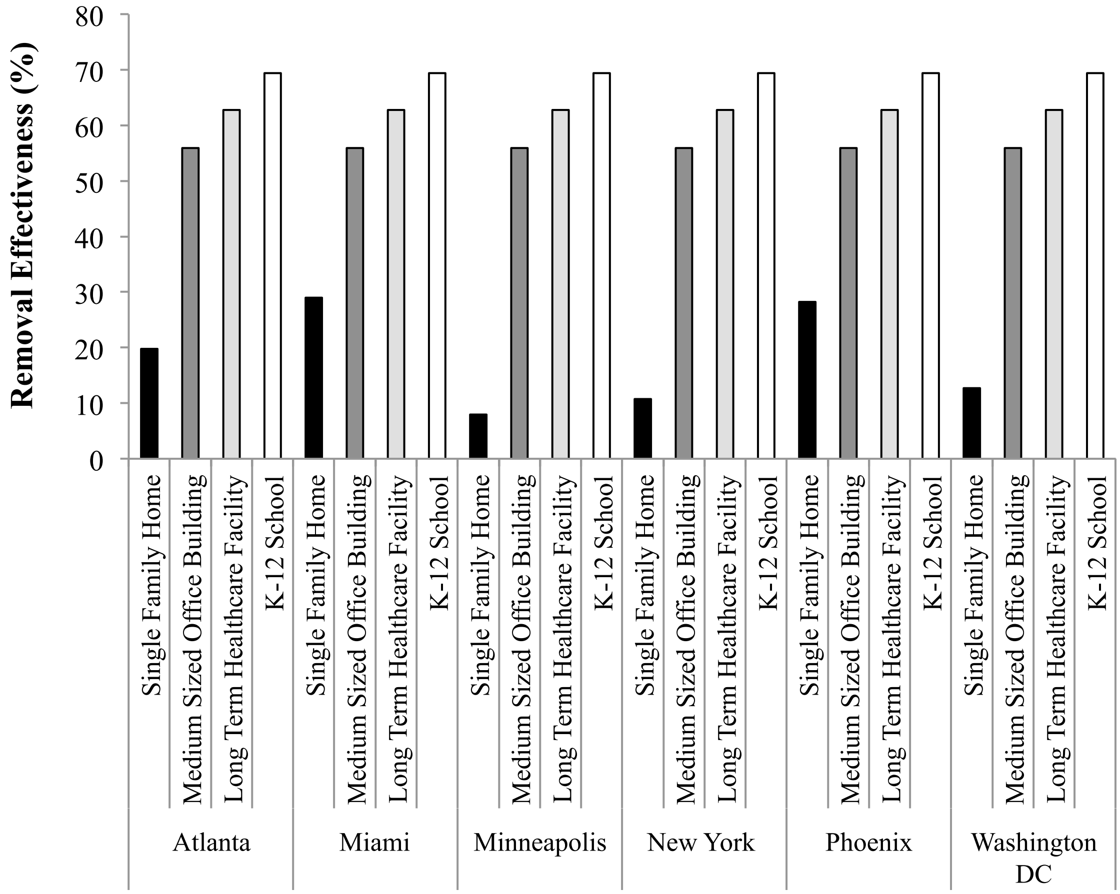

Figure 2. Ozone removal effectiveness when using activated carbon filters in four types of buildings in six of the twelve sample cities.

In the case of single-family homes, cities with high air-conditioning usage during the ozone season (Atlanta, Austin, Houston, Miami, Phoenix, and Riverside) have the highest values of ozone removal effectiveness. The highest effectiveness (just less than 30%) occurs for homes in Miami, and is limited by frequency of HVAC operation and single-pass ozone removal efficiency for the activated carbon filter (assumed 60% for all analyses based on a manufacturer survey).

The ozone removal effectiveness for office buildings is much higher (average of 55%) relative to single-family homes due to the requirement for make-up ventilation air, as well as lower fraction of infiltration toward outdoor-indoor air exchange. The higher indoor ozone concentrations in the absence of carbon filtration and high ozone removal effectiveness in office buildings leads to higher absolute reductions in indoor ozone.

Ozone removal effectiveness in long-term healthcare facilities exceeds 60%. This is primarily due to the large amount of make-up air required for long-term healthcare facilities (50% make-up air) and a relatively low infiltration rate typical of most light commercial buildings (0.2 hr^{-1}). Likewise, K-12 schools also require a relatively large amount of make-up air (at least 25% of supply air), and ozone removal effectiveness exceeded 60% in every city.

Projected Health Benefits

Overall projected health benefits are a function of the ozone removal effectiveness of activated carbon filtration and the demographics of each city. Atlanta, Austin, Houston, Miami, Phoenix, and Riverside have the highest potential health benefits accrued from carbon filter applications due to high air conditioning usage. Conversely, the health benefits of carbon filter usage are relatively low in Buffalo, Chicago, Cincinnati and Minnesota. A majority of the health benefits of reduced ozone are due to reductions in mortality, especially among older populations. Therefore, health benefits are increased in cities with large populations of persons 65 years and older, such as Miami (14% over 65), New York (12% over 65), and Buffalo (12% over 65). Activated carbon filtration may be very beneficial in cities not included in this analysis, and that have a higher fraction of the population over the age of 65 years old. Therefore, in addition to HVAC usage during the summer, health benefits will also be impacted by local demographics, especially the age of the exposed population.

Modeling Results for Single Family Homes

The B/C ratios for applications of activated carbon filters in single family homes in each of 12 target cities are presented in Figure 3. Phoenix and Riverside are the only cities with mean B/C ratios above 1.0. This is primarily due to a combination of high ambient ozone concentration and high air conditioning usage. Although pressure drop is minimized using a 2-inch filter (versus a 1-inch filter), the increased cost of the filter remains an obstacle to an increased B/C ratio. The cost of the filter, as opposed to recurring energy costs, is the primary cost driver for residential carbon filtration, particularly for 2-inch and thicker filters. As such, reduction in the cost differential between conventional particle filters and carbon filters is critical for increasing the B/C ratio. It is expected that as the use of carbon filters become more common, cost differentials will trend toward or even decrease below the lower value.

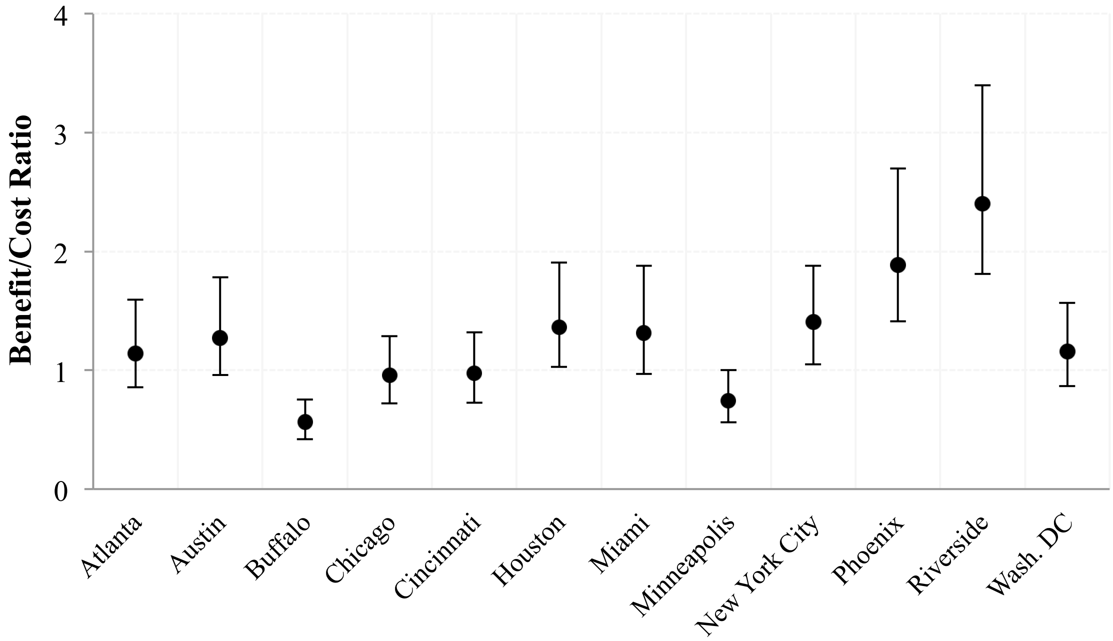

Figure 3. Predicted benefit/cost ratios for residential activated carbon filtration for 2-inch combination filters using two filters per ozone season. The circular symbol represents the mean value for the baseline parameter sets. Range bars represent the 95% confidence intervals of health functions used in the benefit analysis.

Modeling Results for Commercial Office Buildings

The B/C ratios for applications of carbon filters in a medium-sized commercial office building in the 12 target cities are presented in Figure 4. The B/C ratio exceeded unity, even for *least* sensitive receptors (lower 95% confidence interval) in every city and for a large range of filter differential costs, and in some cases exceeded a B/C value of 10. For the most sensitive receptors (upper 95% confidence interval) and mid-range filter differential costs (Figure 4) the B/C ratio exceeded 15 and 20 for Phoenix and Riverside, respectively.

To provide some context of the additional costs of carbon filtration we considered a medium-sized commercial office building in Atlanta, Georgia, during the ozone season (1 May to 30 September). The additional monthly cost (relative to a conventional particle filter) of carbon filtration would range from \$2.75 (1-inch) to \$3.05 (4-inch) per person per ozone season. For the 1-inch filter, 67% of the filtration cost would be due to the increased energy penalty across the filter. For a 4-inch filter, 43% of the filtration costs are attributed to the energy penalty. In comparison, the average seasonal benefits of using carbon filtration in a commercial office building in Atlanta ranges from \$15 to \$32 per person per ozone season.

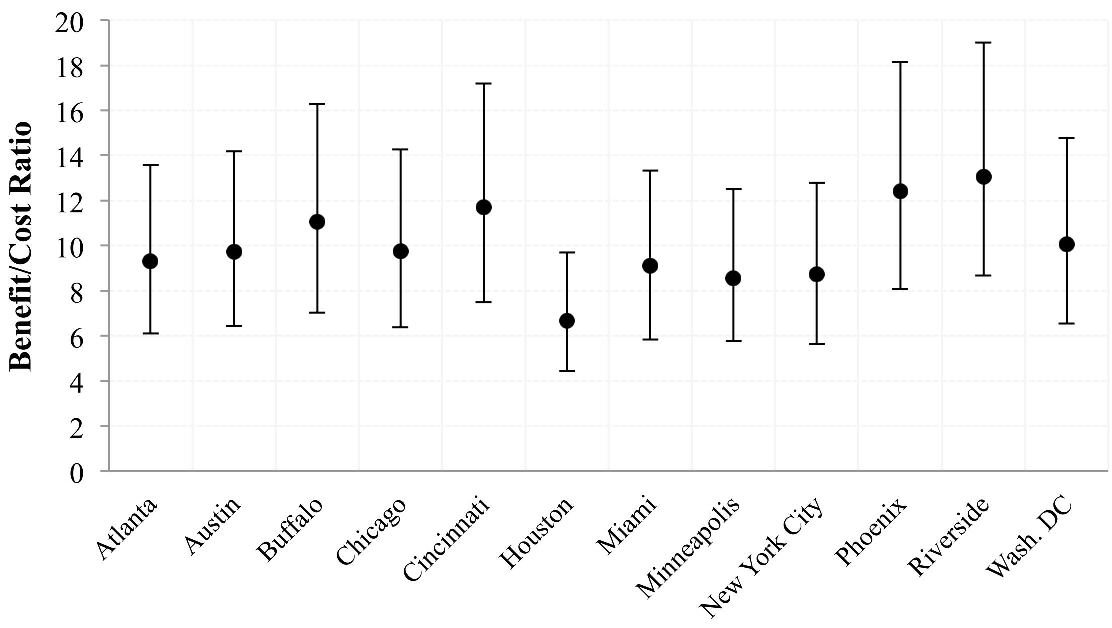

Figure 4. Predicted benefit/cost ratios for activated carbon filtration with a 2-inch combination filter using two filters per ozone season in a medium-sized commercial (office) building. The circular symbol represents the mean value for the baseline parameter sets. Range bars represent the 95% confidence intervals of health functions used in the benefit analysis.

Modeling Results for Long Term Healthcare Facilities

The predicted health benefits of in-duct activated carbon filtration in long term healthcare facilities greatly exceed the other building types considered in this analysis. Demographics are an important consideration. This demographic tends to be the most sensitive to ozone-related health outcomes, particularly premature respiratory mortality; greater than 90% of the benefits are attributed to reduced mortality. The projected number of lives saved annually (Figure 5) exceeds 100 per 100,000 (or 0.1%) for each target city.

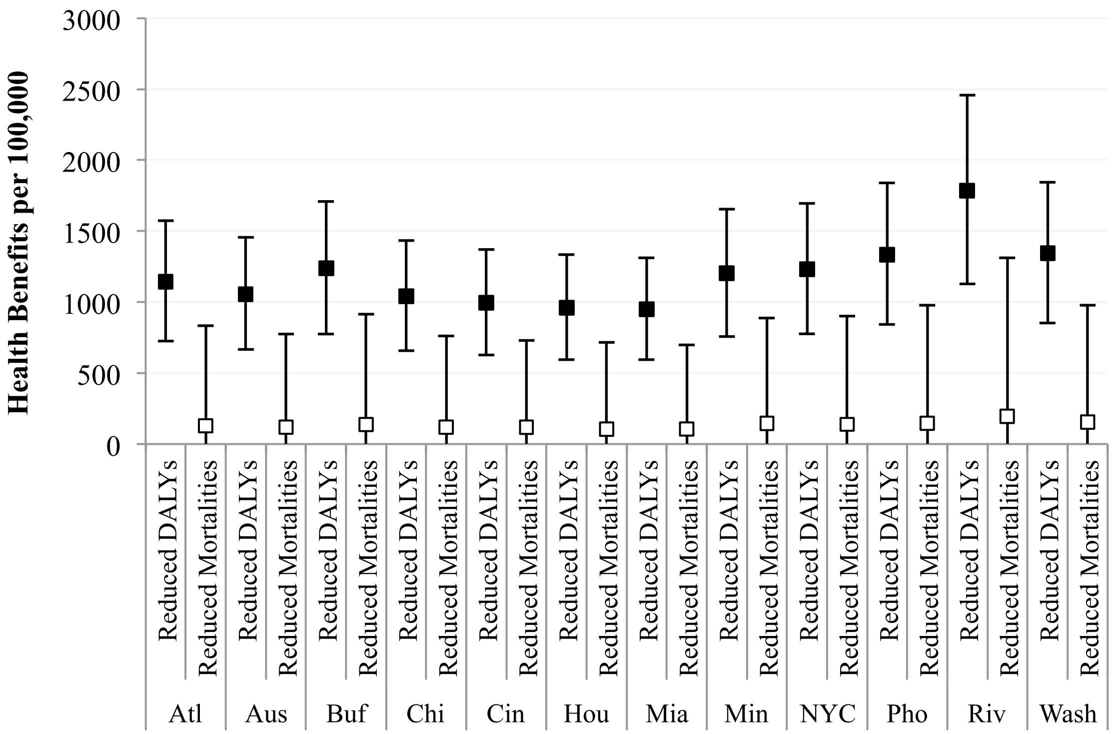

Figure 5. Predicted health benefits of carbon filtration in a long-term healthcare facility. The square symbol represents the mean results of the baseline parameter sets. Range bars represent the 95% confidence intervals of health functions used in the benefit analysis. Only ozone, formaldehyde, and acetaldehyde reductions were considered for the health benefit analysis.

A majority of the health benefits achieved through carbon filtration in long term health care facilities are attributed to reduced mortalities and reduced hospital admissions due to chronic respiratory diseases. A combination of high ozone removal effectiveness and higher respiratory disease prevalence among persons over the age of 65 years yields significant health benefits due to lower ozone exposure. Since the potential benefits are high and the costs are relatively low, B/C ratios are in the hundreds as shown for 2-inch filters in Figure 6.

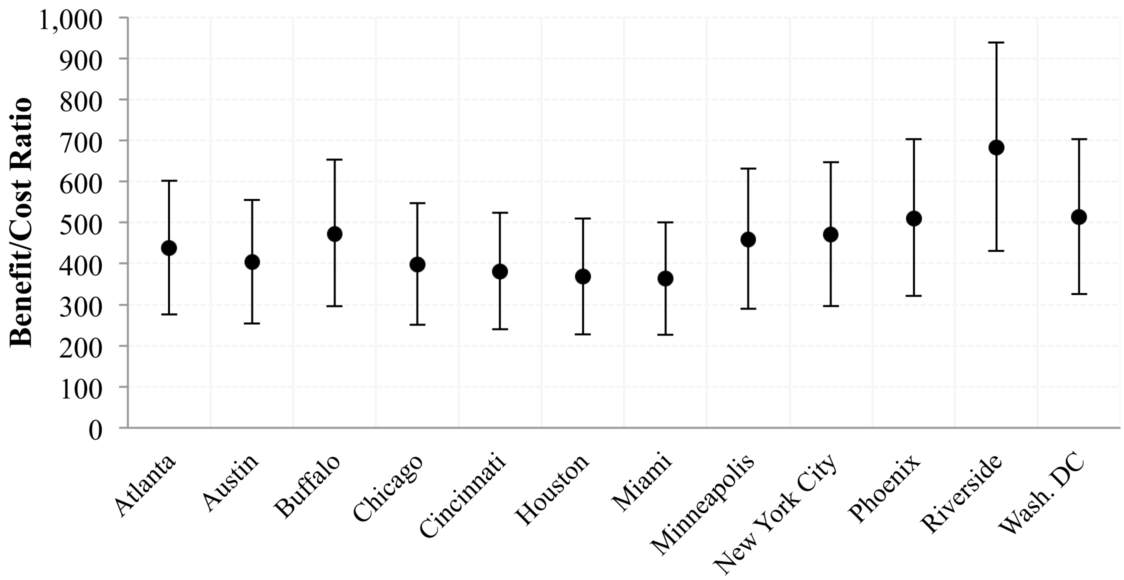

Figure 6. Predicted benefit/cost ratios for activated carbon filtration with a 2-inch combination filter using two filters per ozone season in a long term healthcare facility. The circular symbol represents the mean value of the baseline parameter sets. Range bars represent the 95% confidence intervals of health functions used in the benefit analysis.

Modeling Results for K-12 Schools

The projected school loss days per 100,000 children (with and without activated carbon filtration) in each of the 12 target cities is presented in Figure 7. The overwhelming majority of DALYs saved due to carbon filtration in K-12 schools was attributed to prevented school loss days (99% of all DALYs). Benefit/cost ratios for 2-inch filters are presented in Figure 8.

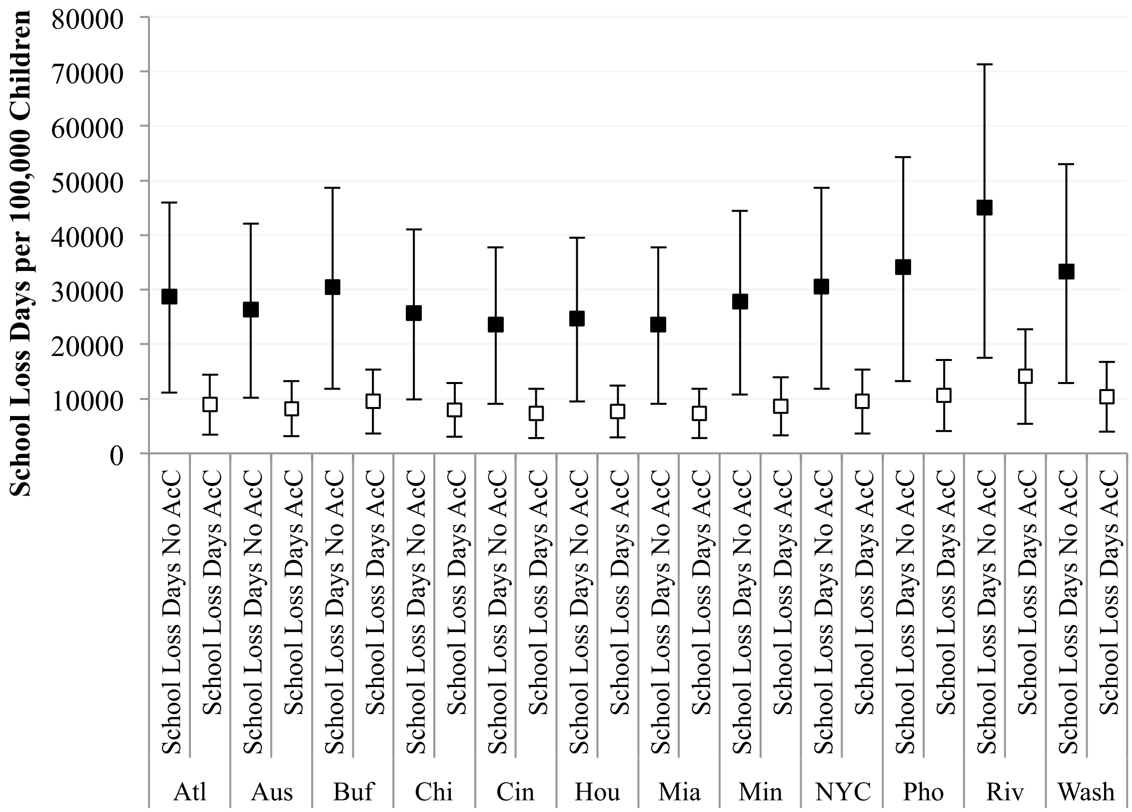

Figure 7. Predicted number of annual school loss days in K-12 schools with and without activated carbon filtration. The square symbol represents the mean results of the baseline parameter sets. Range bars represent the 95% confidence intervals of health functions used in the benefit analysis. Only ozone-related school loss day health functions were considered.

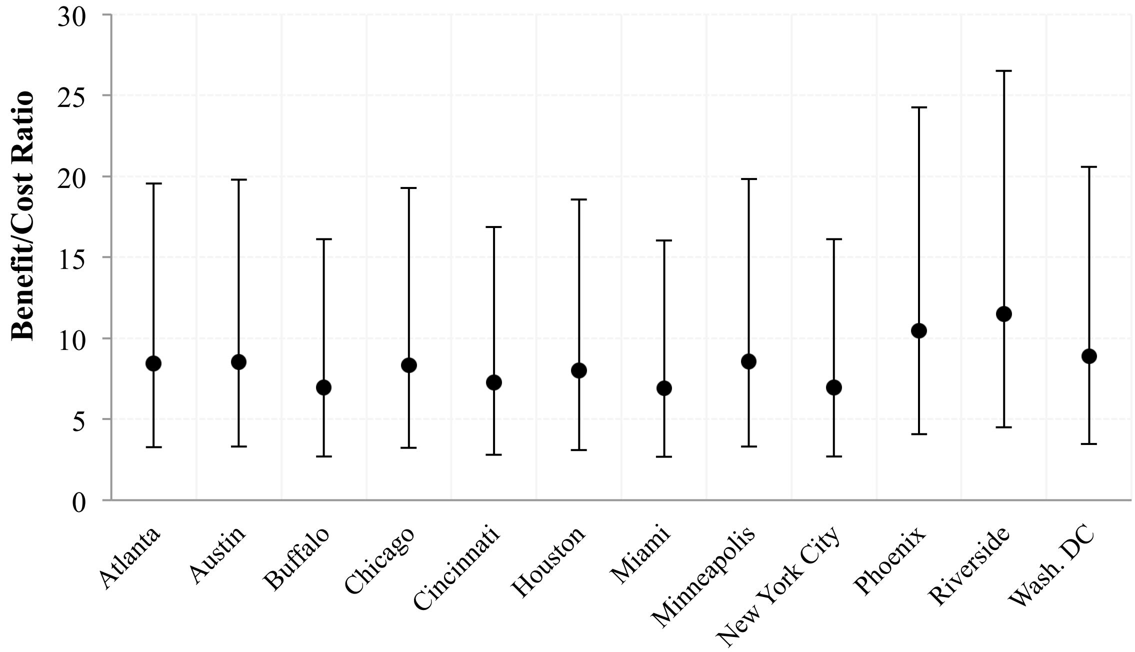

Figure 8. Predicted benefit/cost ratio for activated carbon filtration with a 2-inch combination filter and two filters per ozone season in a K-12 school. The circular symbol represents the mean value of the baseline parameter sets. Range bars represent the 95% confidence intervals of health functions used in the benefit analysis.

The B/C ratio for schools exceeded 1.0 for all 12 target cities for the 2-inch filter and the highest potential benefits were predicted for Riverside (B/C exceeds 11). This is due to high outdoor ozone concentrations relative to the other sample cities. These results suggest that activated carbon filters are currently cost-effective for applications in K-12 schools and will improve school attendance during the summer ozone season.

Conclusion

The overall objective of this project was to complete an assessment of the potential benefits and costs associated with commercially available activated carbon filters in HVAC systems. To complete this task, an integrated systems model was developed to evaluate the benefits and costs of carbon filtration in various types of buildings. Model parameters were based on a number of sources, including the peer-reviewed literature, conference papers, government reports, technology manufacturer websites, and direct communications with filter manufacturers. The major findings of this study indicate that commercially available activated carbon filters are an economically viable strategy for improving health in commercial office buildings, long term healthcare facilities, and K-12 schools. These findings apply to cities that are currently in attainment for USEPA ozone standards and may not require ozone control in accordance with ASHRAE Standard 62.1 (ASHRAE, 2013a). Furthermore, activated carbon filtration in homes results in marginal economic benefits and is best utilized in cities with high seasonal ozone, high HVAC cycling operation, and/or homes with occupants that suffer from respiratory illnesses.

This study does have several limitations that can be improved through future research. There is a lack of published and available gray literature related to long-term performance of activated carbon for removal of ozone, particularly under the highly variable environmental conditions often encountered in practice. Additional limitations and topics for further research include the following:

- Ozone concentrations were averaged across a five-month ozone season. As such, the health effects following high/peak ozone events are not captured. Indoor ozone control during such events would increase the benefit/cost ratios described in this dissertation, particularly for sensitive populations.

- Indoor ozone concentrations are typically much lower than outdoor ozone concentrations, even without specific ozone control technologies. In this study, we assumed that there is no threshold below which incremental reductions in indoor ozone concentration do not have a positive health effect. This is an important issue that has yet to be effectively resolved by the health science community.
- Indoor sources of ozone were also not included in this study. Such sources may be important in offices or schools with poorly maintained and highly operated photocopy machines. For such scenarios the benefit/cost ratio of carbon filters will increase. The integrated systems model developed for this study allows for predictions that include indoor sources of ozone.
- The frequency and time of window opening can affect building occupant exposures to ozone. These factors were omitted from analysis in this study.

Acknowledgements

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reflect the official policy or position of the United States Air Force, U.S. Department of Defense, or the U.S. government.

Appendix C

PAPER III

A Benefit-Cost Analysis of Reduced Ventilation and Carbon Filtration in a University Laboratory Building
(Submitted to *Building and Environment*)

Abstract

This study focused on the benefits and costs of three different experimental ventilation and filtration conditions in a LEED-rated operational campus laboratory tested during two seasons in Austin, TX. Ventilation (i.e., make-up air) flow rates were measured, and energy consumption data were collected in the field and then compared to building energy usage modeled with numerical methods software. The experimental results were then extrapolated to predict energy savings for an entire year. Indoor air quality measurements were collected to determine the potential health consequences of reducing ventilation rates for purposes of lower energy costs. Ventilation reductions in one air-handling unit in the building resulted in nearly $50,000 in reduced chilled water, steam, and fan energy costs per year. A small portion of the savings were then re-invested in activated carbon filters to remove outdoor ozone and improve indoor air quality. A benefit-cost analysis was used to determine that lower ventilation rates combined with activated carbon filtration has potential to reduce ozone-related health costs by 62% and fan energy costs by an additional 21%. This study demonstrates that ventilation reductions in laboratory facilities could yield considerable energy savings, of which a portion could be re-invested in high efficiency activated carbon filtration to improve indoor air quality and occupant health in laboratories.

1. Introduction

The U.S. Energy Information Administration estimates that energy used in buildings accounts for 40% of energy usage nationwide (U.S. Energy Information Administration, 2014). In a life cycle assessment of a university building, operational usage (electricity and HVAC) accounted for over 90% of the building's life cycle energy costs over the 75-year lifetime of the building (Scheuer, et al., 2003). Since buildings account for such a large amount of energy usage, a considerable amount of effort is underway to design more sustainable and energy efficient buildings. Popular building rating systems such as the Leadership in Energy and Environmental Design (LEED) system continue to fuel this trend, but many green building rating systems weigh points more heavily toward energy usage than indoor air quality. For the LEED Commercial Interiors certification (version 3), up to 37 points (out of 110 total points) are awarded for energy savings measures and up to 17 points are awarded for indoor environmental quality (U.S. Green Buildings Council, 2014).

Several researchers have quantified the chronic health impacts (Logue et al., 2012) and life cycle costs (Collinge et al., 2013) of exposure to indoor air pollutants. The projected health and economic benefits of improving indoor air quality can be substantial, ranging from \$17B to \$26B per year (Fisk et al., 2011). One solution to improving indoor air quality while simultaneously saving energy in buildings with high ventilation rates (e.g., laboratories) is to utilize a strategy of lower ventilation rates with improved filtration of outdoor air, specifically by using activated carbon filters.

Fresh-air ventilation rates in university laboratories often exceed 10 air volume changes per hour (10 /hr). Maintaining such a high ventilation rate for laboratories ensures the safety of the occupants against harmful vapors and aerosols. However, since all of the ventilation air is typically exhausted to the atmosphere, all fresh air brought into the building must be conditioned at a significant cost in the form of additional fan energy, chilled water usage, and supply air reheat in the building's heating, ventilating, and air conditioning (HVAC) system. In fact, university laboratories typically consume six to ten times more energy per square foot than comparably sized office buildings (Lawrence Berkeley National Laboratory, 2008).

In this study, we: (1) investigate, with field measurements, changes in indoor air quality and energy usage before and after a significant ventilation reduction, (2) evaluate potential energy savings when comparing the two ventilation scenarios, and (3) determine the life cycle costs and benefits of installing commercially available activated carbon filters.

2. Methods

This study was divided into four phases: (i) calibration of energy monitoring equipment with the building automation system, (ii) winter energy monitoring (two weeks of active sampling), (iii) summer energy and indoor air quality modeling, with and without activated carbon filtration (three weeks of active sampling), and (iv) benefit-cost analyses. Field measurements were limited to three weeks. An illustration showing the phases and conditions of the sampling plan is presented in Figure 1.

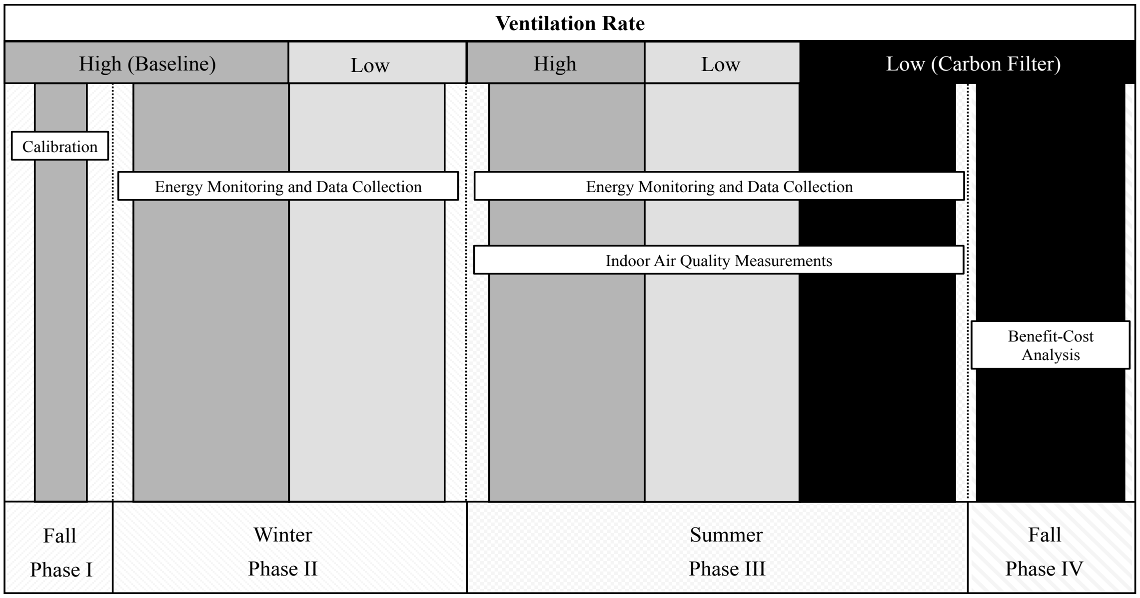


Figure 1. Phases and conditions of the sampling schedule.

2.1. Test Building

Indoor air quality and energy usage due to reduced ventilation rates in a laboratory building on the University of Texas campus were measured. The building selected for this study had laboratory space with very high air exchange rates (as high as 12/hr), as well as sophisticated ventilation control and data collection systems. The building is a 142,000 square foot research facility constructed in 2008 and certified as LEED Silver. It has six primary floors with the top floor acting as the mechanical space for the facility. The first floor is entirely below grade and the second floor is partially below grade. The building has nine air-handling units and 102 separate laboratory heating, ventilating, and air conditioning (HVAC) zones. In addition, all exhaust air from the laboratories is collected and directed through a glycol heat recovery system. The recovered exhaust heat is then used to pre-heat outdoor air before it passes through the heating and cooling coils in the air-handling unit. Ventilation can be remotely controlled and monitored using a building automation system (BAS) (Siemens Insight BAS Software, version 3.13). The operational characteristics of the laboratories served are presented in Table 1.

Table 1. Operational characteristics of the laboratory building.

Modeling and Experimental Parameters		Source
Weather file for energy analysis	Austin, TX	NREL TMY3
Exterior façade (from outside to inside)	2.54 cm thick stone (ST01), 1.91 cm or less air gap (AL11), moisture barrier (BP03)	Building specifications
Interior wall assembly (from outside to inside)	0.95 cm insulator board (IN63), 15.24 cm thick medium weight concrete block (CB27), 1.27 cm gypsum board (GP01)	Building specifications
Roof construction	Steel framing (61 cm on center), no insulation, 1.82 meter overhangs, medium albedo (red tile)	Building specifications
Interior finishes	Acoustic tile for the ceilings, vinyl tile flooring, interior frame walls without insulation, horizontal blinds (medium albedo)	Building specifications
Floor to ceiling height	3.05 meters	Building specifications
Floor to floor height	3.96 meters	Building specifications
Total square footage	2,139 m^2	Building specifications
Ventilation reductions, all labs	13,135 m^3/hr	UT Energy Stewards[1]
Ventilation reductions, five sample labs	3,141 m^3/hr	UT Energy Stewards[1]
Occupancy	24 hours a day, 7 days a week	Informal survey
Function of space	Classrooms and laboratories	Building specifications
Cooling	Chilled water coil	Building specifications
Cooling thermostat set-point	21°C	UT Energy Stewards[1]
Heating	Steam coil, VAV re-heat	Building specifications
Heating thermostat set-point	18°C	UT Energy Stewards[1]
Air-handling unit fan operation	Variable speed	Building specifications
Ventilation supply	Ducted	Building specifications
Exhaust return	Ducted, general exhaust with fume hoods in some labs	Building specifications
Number of air filters in filter bank	24 filters, 61 cm by 61 cm by 48 cm deep bag filters	Building specifications
Filter replacement – maximum pressure drop	400 Pa	Building specifications

(1) The UT Energy Stewards are an office within the University's Facilities Services that focuses on identifying and implementing strategies to reduce energy usage in buildings across campus.

2.2. Calibration and energy field measurements

Three rounds of field measurements were organized to determine overall energy costs at baseline ventilation conditions and at a lower ventilation rate as shown in Table 2. Five rooms on four different floors serviced by a single air-handling unit (AHU) were considered for the analysis. The building is operated all year and was occupied during the field campaign. Airflow measurements from the BAS were verified with field measurements with an airflow capture hood (Airflow Instruments Prohood). Temperature and relative humidity were verified with data loggers (Onset U12-006) placed in the five rooms. During the field experiments the BAS was used to collect temperature and relative humidity data before and after the glycol heat recovery system (pre-heat coil), the heating coil, and the cooling coil in the air-handling unit. Temperature and relative humidity measurements were also collected before and after the reheat coil in the supply ducts servicing each room. Finally, airflow measurements from the BAS were collected for each room (supply and return). Flow rates for both of the ventilation conditions are presented in Table 2.

Table 2. Supply and exhaust air flow rates in each of the five test labs during high and low ventilation conditions.

		High ACH Condition			Low ACH Condition		
Room	Description	Design ACH (1/hr)	Supply (m^3/hr)	General Exhaust (m^3/hr)	Supply (m^3/hr)	General Exhaust (m^3/hr)	Adjusted ACH (1/hr)
Lab 1	Optics Lab	7	850	1189	350	690	4
Lab 2	Teaching Lab	6	1104	1274	693	863	4
Lab 3	Teaching Lab	6	1826	1996	1113	1283	4
Lab 4	Wet Lab	10	2421	2187	1223	989	5
Lab 5	Unoccupied	7	1300	1726	980	1405	6

Each ventilation scenario was run for one to two weeks and in sequence with one another in order to use similar outdoor meteorological conditions. Heating and cooling energy were determined by using measured airflow rates and equations for latent and sensible heat for ventilation air passing through the three heat exchangers in the air-handling unit. Steam usage (kilograms of steam/second) in the AHU heating coil and in the variable air volume re-heat units in each of the labs was calculated using Equation 1. The heat recovered from the glycol recovery system to pre-heat outdoor air was also calculated using Equation 1.

$$Q = \dot{V}\rho c_p \Delta T = \dot{m} h_{fg} \qquad \textbf{(1)}$$

Q = heat energy [kW]

$\dot{V}$ = volumetric air flow rate through the heat exchanger [m^3/sec]

ρ = density of air at standard temperature and pressure (STP) = 1.2754 [kg/m^3]

c_p = specific heat of air at STP = 1.005 [kJ/°C•kg]

ΔT = difference in temperature across the heat exchanger [°C]

$\dot{m}$ = mass flow-rate of steam [kgs/sec]

h_{fg} = latent heat of vaporization = 2,260 [kJ/kg]

The amount of chilled water used in the cooling coil was calculated using Equation 1. Similarly, steam usage in the AHU heating coil and the re-heat coils in the variable air volume units in each laboratory were calculated using air flow rates, the difference in temperature across the coil, and Equation 1. Electrical fan energy was collected from the BAS system, which was reported in kilowatt-hours (kWh). The University of Texas produces its own chilled water, steam, and electricity using a high efficiency chiller and cogeneration. On average, the university pays lower energy costs than most utilities ($0.58 per kWh of chilled water, $0.06 per kWh of electricity, and $0.04 per kilogram of steam). Total energy savings were estimated by taking the difference of calculated energy costs at baseline and reduced ventilation conditions.

2.3. Indoor air quality measurements

Indoor air quality measurements were collected in parallel with the energy field measurements. Pollutants of concern included ozone, particulate matter, and volatile organic compounds (VOCs). Carbon dioxide was also measured.

Volatile organic compounds were collected using Tenax-TA® with thermal desorption and gas chromatography/mass spectrometry (Hewlett-Packard gas chromatograph model number 5890 II outfitted with a HP 5971 mass selective detector).

Each sorption tube was packed with 75 mg of Tenax-TA® sorbent and conditioned in nitrogen at 300°C for two hours. Active sampling was conducted with two pumps in each room during each ventilation condition (Buck Elite-5 Pump 5-6000cc/min 120V). The pumps were programmed at two different pumping rates, 10 mL/min and 40 mL/min, and the sampling time was 4 hours. For every 10 Tenax-TA® samples collected in the field, a lab blank and trip blank were used for baseline analysis. Compounds were identified by using the library compound search in Hewlett Packard ChemStation software and the NIST 11 Mass Spectral Database. The mass of the identified compounds was estimated using 4-bromofluorobenzene as an internal standard and an assumed response ratio of 1.0. Samples were collected using a sampling rate of 25 mL/min for four hours and were collected in accordance with U.S. Environmental Protection Agency (USEPA) methods (TO-17). In addition to sorption tubes, VOCs were also assessed using summa canisters evaluated by an independent laboratory. The summa canister samples were collected for 24-hours using USEPA method (TO-15).

Ozone concentrations were measured with two UV-absorbance ozone analyzers (2B Technologies Inc., Model 202) programmed to ten minute averaging intervals. Both analyzers were cross calibrated before sampling using a calibrated ozone source (2B Technologies Inc, Model 306) and three point calibration. The indoor ozone measurements were collected using a 6 meter piece of PTFE tubing (Fisher Scientific, ¼-inch O.D., 3/8-inch I.D.), which was positioned with the inlet 30 cm below the ceiling in the center of the room. The second ozone analyzer collected outdoor ozone concentration data in the air-handling unit fresh air intake. Outdoor ozone measurements were also collected from the CAMS 3 air quality monitor in northwest Austin (TCEQ, 2014) to compare against ozone measurements collected in AHU-1. The CAMS 3 air quality monitor is about five miles (line of sight) from the university campus.

Due to low concentrations of VOCs in the laboratories, a total VOC (TVOC) concentration was used to quantify VOC concentration. Concentrations of TVOC were estimated using the total mass under the chromatographic spectra curve from a retention time of 6 to 16 minutes, and then using the molecular weight of toluene to convert from the mass concentration to a volumetric concentration expressed in parts per billion by volume (ppbv).

Particulate matter was measured using a six-channel optical particle counter (TSI Aerotrak Model 9306). Measurements were taken continuously in a teaching laboratory during three weeks of ventilation changes. Particles were divided into six size bins based on aerodynamic diameter (d_p). The following bins were selected: $d_p < 0.3$ µm, d_p of 0.3 to 1.0 µm, d_p of 1.0 to 2.5 µm, d_p of 2.5 to 5.0 µm, d_p of 5.0 to 10.0 µm, and $d_p > 10.0$ µm. Measurements were collected using particle counts per cubic meter and measurements were recorded every 30 minutes during the three weeks of field tests. Particle mass was estimated by converting particle number counts assuming a particle density of 1 g/cm^3 and geometric mean d_p for each size bin.

Carbon dioxide (CO_2) concentrations were collected using a Telaire Model 7001 CO_2 monitor. Data were collected in a teaching laboratory over three weeks and measurements were logged every five minutes using a data logger (Onset U12-006). Formaldehyde was also measured using a continuous formaldehyde monitor (Shinyei

FFM-MD), however all of the measurements taken within the building were below the limit of detection of the instrument (10 ppb).

2.4. Cost-benefit analysis: energy savings and indoor pollutant exposure

Indoor air quality in buildings with high ventilation rates is generally dominated by pollution of outdoor origin, e.g., ozone. Exposure to ozone can be harmful to human health. Ozone reacts with polyunsaturated fatty acids in fluids lining the lung with subsequent adverse effects in the airway epithelium (Levy et al., 2001). Additionally, ozone exposure has been linked to respiratory related mortalities and hospital admissions (USEPA, 2012). Finally, a recent study has linked indoor ozone exposure to ozone-related mortalities at relatively low ozone concentrations (Chen et al., 2012).

The predicted health costs of ozone exposure in the laboratory building was estimated using the CO3B-Calc model (Corsi et al., 2014). The CO3B-Calc model employs health-impact functions to determine the economic costs of exposure to harmful air pollutants such as ozone. The health impacts are converted to disability-adjusted life-years (DALYs), which can be monetized (Bobinac et al., 2014). Reductions in exposure to pollutants can thus be translated to a reduction in DALYs, and effective monetary benefit. Occupancy in the laboratories was estimated at 300 people ranging in age from 18 to 24 who occupy the laboratories 20 hours per week for 30 weeks per year (typical academic year). Energy savings are estimated by a combination of modeling and field measurements as described previously.

2.4.1. Activated carbon filtration

Activated carbon filters are known to remove ozone and other outdoor pollutants in operational environments (Ginestet et al., 2013; Shields et al., 1999). Ozone is an oxidizing agent (Weschler, 2004) and reacts with surfaces (heterogeneous reactions) and other gaseous species in bulk air (homogeneous reactions) to yield potentially harmful gaseous by-products such as secondary organic aerosols (SOAs), formaldehyde, acetaldehyde, and hydroxyl radicals (Weschler, 2011). The benefits of carbon filtration include reductions in ozone and ozone reaction products such as SOAs, as well as potential reductions in speciated and total VOCs.

One bank of 24 particle filters that supplies 100% make-up air to laboratories with a maximum design flowrate of 81,600 m^3/hr was replaced with activated carbon filters. The filters were substituted for existing bag filters at the low ventilation rate, and the low ventilation rate was maintained after the carbon filters were installed. The activated carbon filters selected for this study were Koch Filter Corporation Durakleen high efficiency gas phase filters. The face area of the filters was 61 cm x 61 cm and the filters were placed within a rigid sheet metal box that was 30 cm deep. The carbon was composed of coconut shell charcoal with a surface area of 1,100 m^2/g (evaluated using BET method), and the carbon mesh size was 20 x 50. According to the filter manufacturer, no adhesives were used in the carbon filter.

The additional costs of carbon filtration include higher filter costs (compared to bag filters), but this cost is much lower than the cost savings due to energy reductions from lower ventilation rates in the laboratories.

3. Results and Discussion

3.1. Energy field measurements

Energy field measurements were collected over two seasons, late winter/early spring, and late summer/early fall. The first collection period lasted nearly three weeks, with one week at high ventilation rate and two weeks at the reduced ventilation rate. The second collection period lasted three weeks and included three test scenarios: one week at baseline (high) ventilation rate, one week at reduced ventilation rate, and one week at reduced ventilation rate with activated carbon filtration.

During the winter tests, it was determined that the glycol recovery heat exchanger was fully operational and was effectively pre-heating cold outdoor air using recycled exhaust air. Average hourly energy costs for the five labs were compared using a two-sample one-tailed statistical t-test. In the comparison, energy costs decreased by 35% (ρ <0.00001) during the winter ventilation reductions.

The glycol heat exchanger was not operational during the summer test experiments. However, the ventilation reductions still resulted in energy savings. Average hourly energy costs for the five test labs decreased by 3% (ρ <0.00001) between the high and low ventilation conditions during the summer tests. The savings were more substantial when comparing the high condition to the low ventilation rate combined with carbon filters. Average hourly energy costs decreased by 12% (ρ <0.00001) between the low ventilation condition with and without carbon filters, and 14% (ρ <0.00001) when comparing the high ventilation condition versus the low condition with carbon filters. This is likely attributable to reductions in fan energy as the new carbon filters have a lower initial pressure drop (25 Pa) than the bag filters that were previously installed (100 Pa). The fan energy savings were substantial, and average fan energy decreased by 5% (ρ <0.00001) between the high and low ventilation conditions, and 21% (ρ <0.00001) between the low ventilation condition versus low ventilation with carbon filters. Average fan energy decreased by 25% (ρ <0.00001) when comparing the high ventilation condition versus the low condition with carbon filters.

Data from both the winter and summer tests were analyzed to estimate annual cost savings from the ventilation reductions. The analysis included energy savings with and without the glycol heat recovery system. Two polynomial expressions (with heat recovery and without heat recovery) were applied to the data using statistical tools in SPSS software (IBM Corporation, 2013). Outdoor temperature was used as the dependent variable and annual energy cost was the independent variable in the analysis. The annual energy costs with and without heat recovery are shown in Figure 2 as a function of outdoor temperature. The polynomial relationships are shown in Equations 4 and 5 below, and are specific to the building tested.

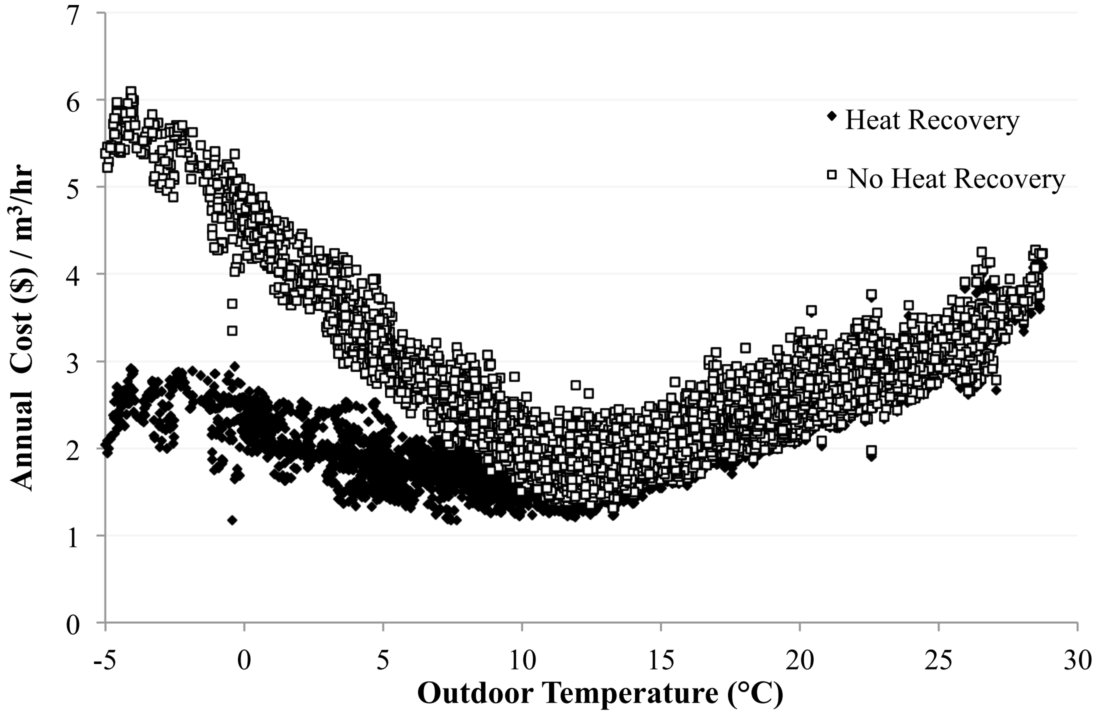


Figure 2. Annual cost per cubic foot per minute of ventilation air in the laboratory building versus outdoor dry bulb temperature.

Energy Cost ($) / m^3/hr (no heat recovery)

$$= 0.0002(T_{out})^3 + 0.0178(T_{out})^2 - 0.3897(T_{out}) + 4.4434 \quad \textbf{(4)}$$

Energy Cost ($) / m^3/hr (heat recovery)

$$= 0.00007(T_{out})^3 + 0.0083(T_{out})^2 - 0.1264(T_{out}) + 2.1816 \quad \textbf{(5)}$$

Where T_{out} is the outdoor dry-bulb temperature in degrees Celsius.

Both polynomial relationships were analyzed hourly using TMY3 meteorological data (Wilcox and Marion, 2008) for Austin, TX. The average annual energy costs per m^3/hr of ventilation air were also estimated. For the five test laboratories, the estimated ventilation reductions were 3,141 m^3/hr , leading to $11,315 in annual energy savings. For all forty rooms served by the AHU, the estimated ventilation reductions were 13,135 m^3/hr, leading to $47,300 in annual energy savings.

3.2. Indoor air quality

Quantification of individual VOCs using Tenax-TA sorbent tubes was difficult because of the low concentrations of VOCs in the laboratories. Therefore, a total VOC (TVOC) concentration was used to quantify VOC concentrations for samples collected on Tenax-TA sorbent tubes. An average increase of 72% ($\rho < 0.05$) from 6.3 ppb to 10.9 ppb in TVOC was observed when the ventilation rate was reduced from the high to low condition.

Specific VOCs were identified and quantified in subsequent testing using summa canisters and TO-15 collection methods analyzed by an independent laboratory. The three VOCs with highest concentrations included dichloromethane, n-hexane, and toluene. The concentrations of VOCs did not vary considerably between the low ventilation condition and the low ventilation condition with carbon filtration, indicating that most of the VOCs measured during the sampling period were emitted from indoor sources in the laboratories. The highest measured concentrations of VOCs are presented in Table 3 with indicators showing at which ventilation condition the highest measurement was collected.

Summa canisters were also collected before and after the bag filters and the carbon filters during the low ventilation condition. The bag filters were sources of TVOCs, with an outlet (post filter) TVOC concentration 17% higher than the inlet (pre-filter) concentration ($\rho < 0.05$). The carbon filters removed VOCs; the outlet (post filter) concentration was 62% lower than the inlet (pre-filter) concentration ($\rho < 0.05$).

Table 3. Highest recorded VOC concentrations in five sample laboratories.

		Highest Measured Concentration ($\mu g/m^3$)					
Volatile Organic Compound	CAS Registry Number	Lab 1	Lab 2	Lab 3	Lab 4	Lab 5	Outdoor
Chloromethane	74-87-3	0	1^{LV}	1^{LV}	2^{LV}	2^{LV}	2^{LV}
Acetonitrile	75-05-8	2^{LV}	1^{LV}	1^{LV}	1^{LV}	0	0
Dichloromethane	75-09-2	19^{LV}	10^{LV}	9^{LV}	3^{LC}	7^{LV}	7^{LV}
2-Butanone (MEK)	78-93-3	0	3^{LV}	3^{LC}	2^{HV}	0	2^{HV}
n-Hexane	110-54-3	14^{LV}	8^{LV}	5^{LV}	9^{LV}	5^{LV}	4^{LV}
Cyclohexane	110-82-7	0	0	6^{LC}	4^{HV}	0	0
Toluene	108-88-3	3^{LV}	28^{LV}	29^{LV}	2^{HV}	6^{LV}	3^{LV}
Tetrahydrofuran	109-99-9	0	0	0	0	0	3^{LV}

HV = High Ventilation
LV = Low Ventilation
LC = Low Ventilation with Carbon Filters

In the absence of indoor sources, lower ventilation rates should generally lead to a lower indoor/outdoor (I/O) ozone concentration ratio. However, in this study the I/O ozone concentration ratio (Figure 2) increased by an average of 23% ($\rho < 0.05$) under the reduced ventilation scenario, and the average indoor ozone concentration across the five rooms increased by roughly 10 parts per billion, or 56% ($\rho < 0.05$) (Figure 3). The increase in ozone in the laboratories under reduced ventilation conditions is likely due to decreased ozone deposition to surfaces caused by the lower air velocity in the room, the increased role of indoor ozone sources, e.g., photocopy machines, at lower ventilation rates or some combination of the two. In addition, all of the labs are negatively pressurized in comparison to adjoining rooms and hallways, many of which were supplied by a different air-handling unit.

When the activated carbon filters were installed in the air-handling unit at a low ventilation condition, the average indoor/outdoor ozone concentration ratio decreased by 45% ($\rho < 0.05$) compared to the low ventilation condition without carbon filters. The indoor/outdoor ozone concentration ratio was on average 33% lower ($\rho < 0.05$) with the carbon filters installed compared to the high ventilation condition without activated carbon filtration. This result indicates that activated carbon filters can be effective at reducing indoor ozone concentrations. In addition, installation of the activated carbon filters will reduce exposure to ozone reaction products, and could potentially lead to reductions in symptoms of sick building syndrome (Apte et al., 2008). Finally, replacing the existing bag filters with activated carbon filters could provide additional health benefits due to reduced ozone-initiated reactions with the bag filters (Buchanan et al., 2008).

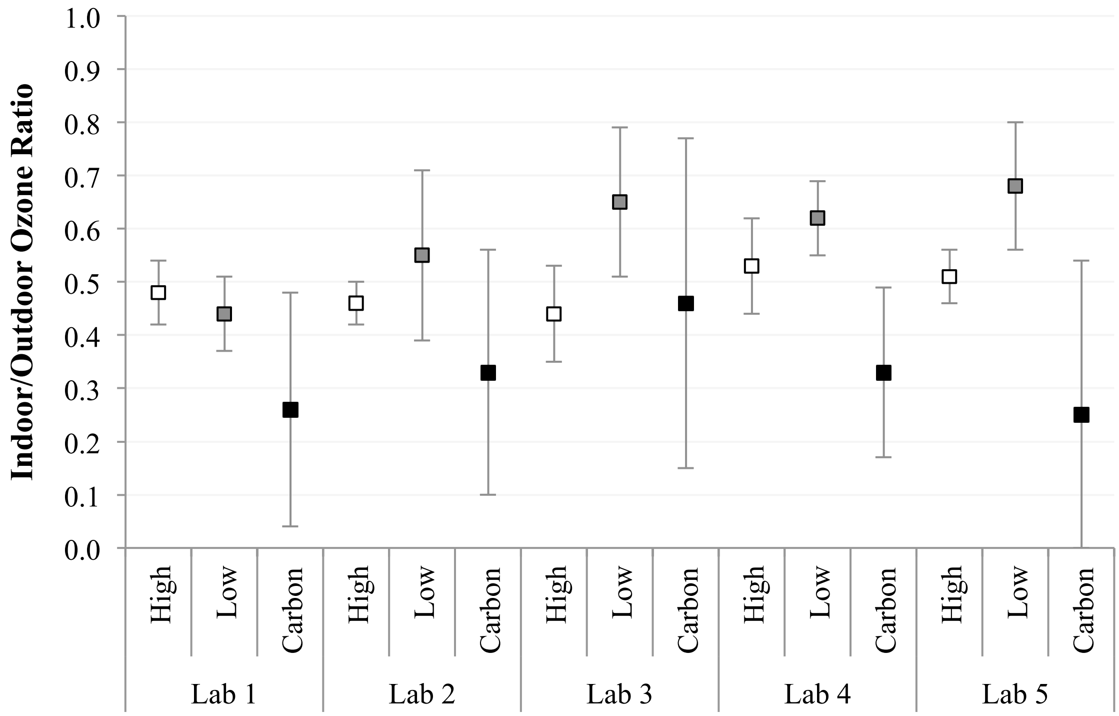


Figure 3. Indoor/outdoor ozone concentration ratios in five sample laboratories building three testing conditions.

Observed concentrations of particles in the laboratories were generally very low under all three experimental conditions. For PM_{10} (d_p < 10 μm), average absolute mass concentrations increased from 0.24 μg/m^3 (high ventilation) to 0.40 μg/m^3 (low ventilation), and to 0.99 μg/m^3 (low ventilation with carbon filter). The average outdoor $PM_{2.5}$ concentrations in the Austin area during the experiments were 5.2 μg/m^3 (σ = 2.5 μg/m^3) (TCEQ, 2014). In contrast, the average indoor $PM_{2.5}$ concentration at high ventilation was 0.023 μg/m^3 (σ = 0.016 μg/m^3), the average indoor $PM_{2.5}$ concentration at low ventilation was 0.030 μg/m^3 (σ = 0.017 μg/m^3), and the average indoor $PM_{2.5}$ concentration with carbon filtration was 0.162 μg/m^3 (σ = 0.106 μg/m^3). The much lower indoor $PM_{2.5}$ concentrations relative to background are a result of make-up air filtration and particle deposition to indoor surfaces.

A boxplot of the distributions of particle measurements under all three experimental conditions is presented in Figure 4. Particle concentrations may have increased somewhat under the carbon filter test scenario due to a combination of carbon dust detaching from the carbon filters and lower deposition rates for particles, likely because of more quiescent conditions in the laboratories. Finally, some accumulated dust was likely released from the cooling and heating coils during and after the filter change.

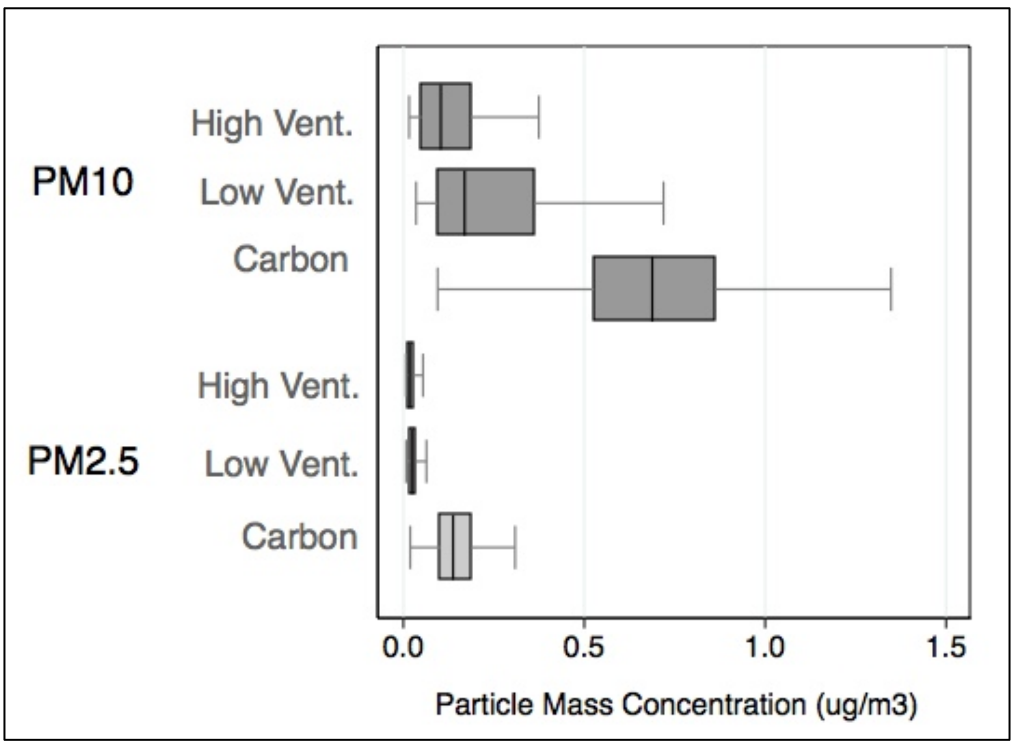


Figure 4. Summary of particle mass concentrations in five sample laboratories under three testing conditions. Boxes show 25th percentile, median, and 75th percentile of measurements. Whiskers represent 1.5 times the interquartile range.

Carbon dioxide (CO_2) measurements did not change significantly during the three experimental conditions (Figure 5). There was an average CO_2 concentration increase of 19% between the high and low conditions ($\rho < 0.01$). However, the average difference in CO_2 concentrations was not statistically significant between the low condition and the low condition with carbon filters ($\rho = 0.14$), an expected result given the inert nature of CO_2. In all cases, the CO_2 measurements were less than 1,000 ppm, which is below the recommended concentrations for indoor environments (ASHRAE, 2010).

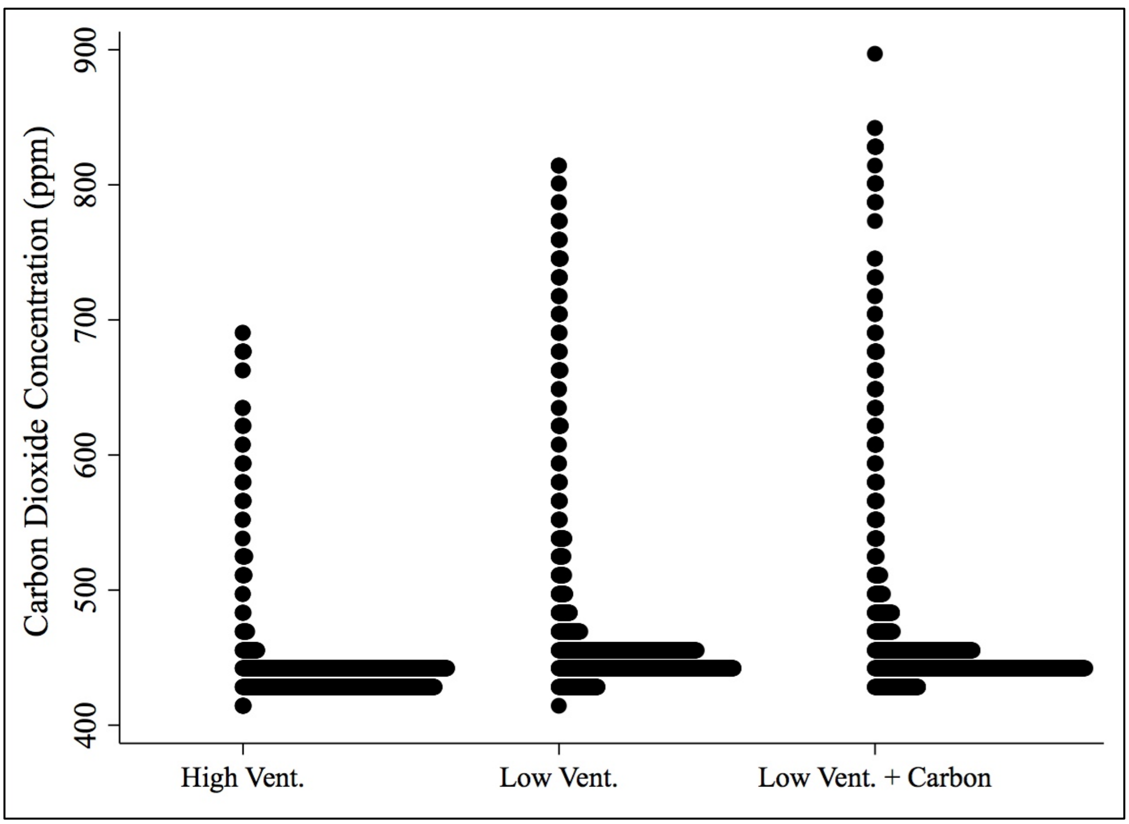


Figure 5. Summary of CO_2 concentrations in five sample laboratories under three testing conditions. The dotplot shows the distribution of measurements taken over the three experimental conditions.

3.4. Cost-benefit analysis results

Results from the ozone field measurements and data collected from the building specifications were used to calibrate the CO3B-Calc model, e.g., to estimate factors such as the ozone deposition loss rate. Comparing model results with the field measurements, it was estimated that the ozone deposition loss rate was approximately 5.0 /hr at high ventilation rates, and 1.2 /hr at low ventilation rates. The difference is likely attributed to a reduction in air turbulence in the rooms due to lower ventilation flow rates. Weschler (2000) observed ozone deposition loss rates as low a 0.8 /hr in a telephone office and as high as 7.6 /hr in a cleanroom, indicating that the estimates are within the range of values found in previous experiments of similar type buildings. Sabersky et al. (1973) also investigated ozone decay rates in several types of buildings and found that HVAC system operation plays an important role in ozone decay to surfaces as ozone decay rates in a home were nearly double when the HVAC system was on compared to when the HVAC system was off.

Field measurements of the carbon filters installed in the laboratory building confirmed a single pass removal efficiency of greater than 70% for ozone after one month of continuous service. Fisk (2009) measured similar single pass removal efficiencies in an office building using activated carbon filters. In his study, activated carbon filters were able to maintain a single pass removal efficiency for ozone of 60% after two months of operation. The filters were exposed to recirculated building air for the first month, followed by one month of exposure to 100% outdoor air.

Filter and labor costs were estimated from discussions with university maintenance staff and a filter retailer. Typical filter replacement of bag filters takes place nearly every 3 months. The carbon filters installed in the laboratory building have a much lower pressure drop than the bag filters previously used for particle removal, and are expected to last at least 6 months before replacement is required. Annual fan energy costs were extrapolated from fan energy costs measured during the three experimental conditions. In addition to pressure drop across the filters, the fan must pull air across three sets of heat exchangers resulting in substantial fan energy costs and estimated total pressure drops ranging from 280 to 320 Pascals.

Annual DALYs due to ozone exposure were estimated using the CO3B-Calc model. Health costs were estimated using a value of $150,000 per DALY (Bobinac et al., 2014).

Parameters for CO3B-Calc application, and estimated net annual costs for filtration and filtration plus health for the three experimental conditions are presented in Table 3. A key takeaway is the net annual filtration costs (last two rows in Table 3). Although activated carbon filters are more expensive than the existing bag filters on a per filter basis, the activated carbon filters have lower fan energy costs and replacement frequency. In the case of the test building, the net additional annual costs of activated carbon filtration are approximately $1,500 per year. This is less than 5% of the energy savings gained by reducing the ventilation rates, resulting in net energy savings of $45,000 per year. Additional benefits of activated carbon filtration include the health benefits gained due to reduced ozone exposure in the building. When considering the monetary value of these health benefits, the net annual filtration cost with activated carbon filters is less than net annual filtration costs for both the high and low ventilation conditions when using the existing bag filters. This strategy demonstrates that energy savings and improvements in indoor air quality are not mutually exclusive, especially after the installation of activated carbon filters. Furthermore, this strategy should be considered for other types of buildings that require substantial quantities of ventilation air, such as commercial office buildings, K-12 schools, and healthcare facilities.

Table 3. CO3B-Calc parameter inputs for three experimental conditions resulting in net annual costs of filtration and health.

CO3B-Calc Parameter Inputs and Results	**High Ventilation**	**Low Ventilation**	**Low Ventilation with Carbon**
Volume	6,519 m^3	6,519 m^3	6,519 m^3
Ventilation Supply	41,965 m^3/hr	28,831 m^3/hr	28,831 m^3/hr
Exhaust Flowrate	51,330 m^3/hr	38,196 m^3/hr	38,196 m^3/hr
Occupancy	300 people	300 people	300 people
Average Time in Building	7%	7%	7%
Ozone Deposition Loss Rate	5.0 /hr	1.2 /hr	1.2 /hr
Single Pass Ozone Removal in Air Filters	10%	10%	70%
Average Outdoor Ozone Concentration	28 ppb	28 ppb	28 ppb
Average Indoor Ozone Concentration	13 ppb	16 ppb	6 ppb
Filter Replacement Cost	$50	$50	$150
Replacement Frequency	4X per year	4X per year	2X per year
Number of Filters in Filter Bank	24 filters	24 filters	24 filters
Labor Installation Costs	$66	$66	$132
Annual Fan Energy Costs	$7,008	$6,132	$5,256
DALYS due to Ozone Exposure	0.0159	0.0195	0.0074
Annual Health Costs due to Ozone Exposure	$2,385	$2,925	$1,110
Net Annual Costs (Filtration)	**$12,072**	**$11,196**	**$12,720**
Net Annual Costs (Filtration and Health)	**$14,457**	**$14,121**	**$13,830**

4. Conclusion

Ventilation reductions in a large academic laboratory facility can net significant energy savings. This strategy could be implemented in newer laboratory buildings that allow for the automated control and monitoring of make-up air. Estimated annual energy savings in the 40 rooms supplied by AHU-1 in the laboratory building described herein would be approximately $47,000 per year when the reduced ventilation condition is maximized (i.e, within equipment tolerances).

Health benefits can also be achieved if a small percentage (on the order of 5% or less) of energy savings are used to improve indoor air quality by application of activated carbon filters to treat supply air for ozone. The activated carbon filters used in this study also reduced fan energy when compared to traditional bag filters. The combined annual costs of filtration (energy, capital, and labor costs) and health when utilizing activated carbon filters are approximately 4% lower than the baseline condition resulting in a combined net benefit of $47,488 per year when the filters are employed in conjunction with reduced ventilation strategies. The most important takeaway of this study is that it is possible to simultaneously garner energy savings and improve indoor air quality in operational laboratories when reinvesting a portion of the energy savings in high efficiency activated carbon filtration.

Further studies are warranted to validate the potential for simultaneous reduction in building energy use and improved indoor air quality. A scoping analysis of the net benefits across highly ventilated laboratory buildings in different climate zones would be beneficial in the future to assess large-scale potential for building energy use and it's effects on public health.

Acknowledgements

The University of Texas Green Fee Committee funded this study and provided tuition support to Josh Aldred. This study was conducted in collaboration with the University of Texas Environmental Health and Safety office and the University of Texas Energy Stewards. Additional financial support was provided through an ASHRAE Student Grant-in-Aid, the Walter L. and Reta Mae Moore Graduate Fellowship in Water Resources at the University of Texas at Austin, and the U.S. Air Force. The views expressed in this article are those of the author and do not reflect the official policy or position of the United States Air Force, U.S. Department of Defense, or the U.S. government.

Appendix D

```
%Code for MC analysis of 12 U.S. cities
%Key outputs include B/C ratio, delta DALYs, delta O3 indoors
%Residential penetration factor estimated from Stephens et al. (2012)
%Environmental Science and Technology Journal

pd = makedist('Normal', 'mu', 0.79, 'sigma', 0.13);
t = truncate(pd, 0, 1);
Y = random(t, 100000, 1);
P = Y;

%Residential infiltration data estimated from Persily et al. (2010)
Indoor Air Journal

%Atlanta mu and sigma 0.48  0.25
%Austin  mu and sigma 0.42  0.25
%Buffalo mu and sigma 0.41  0.29
%Chicago mu and sigma 0.42  0.31
%Cincinn mu and sigma 0.42  0.31
%Houston mu and sigma 0.42  0.25
%Miami   mu and sigma 0.48  0.25
%Minneap mu and sigma 0.45  0.33
%NYC     mu and sigma 0.41  0.29
%Phoenix mu and sigma 0.50  0.23
%Riversi mu and sigma 0.40  0.21
%Wash DC mu and sigma 0.48  0.25

pd = makedist('Normal', 'mu', 0.48, 'sigma', 0.25);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Atl_Inf = Y;

pd = makedist('Normal', 'mu', 0.42, 'sigma', 0.25);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Aus_Inf = Y;

pd = makedist('Normal', 'mu', 0.41, 'sigma', 0.29);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Buf_Inf = Y;

pd = makedist('Normal', 'mu', 0.42, 'sigma', 0.31);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Chi_Inf = Y;

pd = makedist('Normal', 'mu', 0.42, 'sigma', 0.31);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Cin_Inf = Y;
```

```
pd = makedist('Normal', 'mu', 0.42, 'sigma', 0.25);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Hou_Inf = Y;

pd = makedist('Normal', 'mu', 0.48, 'sigma', 0.25);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Mia_Inf = Y;

pd = makedist('Normal', 'mu', 0.45, 'sigma', 0.33);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Min_Inf = Y;

pd = makedist('Normal', 'mu', 0.41, 'sigma', 0.29);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
NYC_Inf = Y;

pd = makedist('Normal', 'mu', 0.50, 'sigma', 0.23);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Phx_Inf = Y;

pd = makedist('Normal', 'mu', 0.40, 'sigma', 0.21);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Riv_Inf = Y;

pd = makedist('Normal', 'mu', 0.48, 'sigma', 0.25);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Wsh_Inf = Y;

A = [Atl_Inf Aus_Inf Buf_Inf Chi_Inf Cin_Inf Hou_Inf Mia_Inf Min_Inf
NYC_Inf Phx_Inf Riv_Inf Wsh_Inf];
Infiltration = A;

datasum=prctile(Infiltration,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Infiltration.xlsx';
xlswrite(filename, datasum);

%Single pass removal efficiency for carbon filters estimated from field
%experiments

pd = makedist('Uniform','Lower',.5,'Upper',.7);
Y = random(pd, 100000,1);
fO3 = Y;
```

```
%Summer HVAC cycling estimated from LBNL data using # AC compressor
hours

pd = makedist('Uniform','Lower',.11,'Upper',.31);
Y = random(pd, 100000,1);
Atl_Hon = Y;

pd = makedist('Uniform','Lower',.20,'Upper',.40);
Y = random(pd, 100000,1);
Aus_Hon = Y;

pd = makedist('Uniform','Lower',0,'Upper',.13);
Y = random(pd, 100000,1);
Buf_Hon = Y;

pd = makedist('Uniform','Lower',0,'Upper',.17);
Y = random(pd, 100000,1);
Chi_Hon = Y;

pd = makedist('Uniform','Lower',.01,'Upper',.21);
Y = random(pd, 100000,1);
Cin_Hon = Y;

pd = makedist('Uniform','Lower',.20,'Upper',.40);
Y = random(pd, 100000,1);
Hou_Hon = Y;

pd = makedist('Uniform','Lower',.28,'Upper',.48);
Y = random(pd, 100000,1);
Mia_Hon = Y;

pd = makedist('Uniform','Lower',0,'Upper',.17);
Y = random(pd, 100000,1);
Min_Hon = Y;

pd = makedist('Uniform','Lower',0,'Upper',.20);
Y = random(pd, 100000,1);
NYC_Hon = Y;

pd = makedist('Uniform','Lower',.27,'Upper',.47);
Y = random(pd, 100000,1);
Phx_Hon = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.29);
Y = random(pd, 100000,1);
Riv_Hon = Y;

pd = makedist('Uniform','Lower',.02,'Upper',.22);
Y = random(pd, 100000,1);
```

```
Wsh_Hon = Y;

% 100% fan operation option

%Atl_Hon = wons;
%Aus_Hon = wons;
%Buf_Hon = wons;
%Chi_Hon = wons;
%Cin_Hon = wons;
%Hou_Hon = wons;
%Mia_Hon = wons;
%Min_Hon = wons;
%NYC_Hon = wons;
%Phx_Hon = wons;
%Riv_Hon = wons;
%Wsh_Hon = wons;

A = [Atl_Hon Aus_Hon Buf_Hon Chi_Hon Cin_Hon Hou_Hon Mia_Hon Min_Hon
NYC_Hon Phx_Hon Riv_Hon Wsh_Hon];
Cycling = A;

datasum=prctile(Cycling,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Cycling.xlsx';
xlswrite(filename, datasum);

%Outdoor ozone data from NMMAPs and USEPA
pd = makedist('Normal', 'mu', 31, 'sigma', 21);
t = truncate(pd, 2,114);
Y = random(t, 100000, 1);
Atl_O3 = Y;

pd = makedist('Normal', 'mu', 33, 'sigma', 17);
t = truncate(pd, 2,105);
Y = random(t, 100000, 1);
Aus_O3 = Y;

pd = makedist('Normal', 'mu', 35, 'sigma', 17);
t = truncate(pd,2,95);
Y = random(t, 100000, 1);
Buf_O3 = Y;

pd = makedist('Normal', 'mu', 31, 'sigma', 17);
t = truncate(pd, 2,139);
Y = random(t, 100000, 1);
Chi_O3 = Y;

pd = makedist('Normal', 'mu', 36, 'sigma', 19);
t = truncate(pd, 2,112);
Y = random(t, 100000, 1);
Cin_O3 = Y;
```

```
pd = makedist('Normal', 'mu', 23, 'sigma', 18);
t = truncate(pd,2,131);
Y = random(t, 100000, 1);
Hou_O3 = Y;

pd = makedist('Normal', 'mu', 27, 'sigma', 10);
t = truncate(pd, 2,101);
Y = random(t, 100000, 1);
Mia_O3 = Y;

pd = makedist('Normal', 'mu', 32, 'sigma', 15);
t = truncate(pd, 2,102);
Y = random(t, 100000, 1);
Min_O3 = Y;

pd = makedist('Normal', 'mu', 28, 'sigma', 16);
t = truncate(pd, 2,121);
Y = random(t, 100000, 1);
NYC_O3 = Y;

pd = makedist('Normal', 'mu', 39, 'sigma', 19);
t = truncate(pd, 2,98);
Y = random(t, 100000, 1);
Phx_O3 = Y;

pd = makedist('Normal', 'mu',47, 'sigma',21 );
t = truncate(pd, 2,127);
Y = random(t, 100000, 1);
Riv_O3 = Y;

pd = makedist('Normal', 'mu', 33, 'sigma', 18);
t = truncate(pd, 2,102);
Y = random(t, 100000, 1);
Wsh_O3 = Y;

%Average Recirculation Rates - Stephens et al. (2011) Building and
Environ.

pd = makedist('Normal', 'mu', 7.6, 'sigma', 6.7);
t = truncate(pd, 4.3, 32.5);
Y = random(t, 100000,1);
Recirc = Y;
% adjustment factor since truncating oversampled higher values and
raised the mean/median
Recirc = Recirc./1.45;

%Ozone surface loss rates - Lee et al. (1999) and Sabersky et al.
(1973)
pd = makedist('Normal', 'mu', 2.8, 'sigma', 1.3);
t = truncate(pd,0,15);
```

```
Y = random(t, 100000, 1);
AC_off_SR = Y;

pd = makedist('Normal', 'mu', 5.4, 'sigma', 2.5);
% didn't have a sigma for Sabersky 1973 so estimated based on ratio
between mu and sigma from
% Lee et al. (1999)
t = truncate(pd,0,20);
Y = random(t, 100000, 1);
AC_on_SR = Y;

%City specific ozone surface loss rates
wons = ones(100000,1);

Atl_SR = (Atl_Hon.*AC_on_SR) + (wons - Atl_Hon).*AC_off_SR;

Aus_SR = (Aus_Hon.*AC_on_SR) + (wons - Aus_Hon).*AC_off_SR;

Buf_SR = (Buf_Hon.*AC_on_SR) + (wons - Buf_Hon).*AC_off_SR;

Chi_SR = (Chi_Hon.*AC_on_SR) + (wons - Chi_Hon).*AC_off_SR;

Cin_SR = (Cin_Hon.*AC_on_SR) + (wons - Cin_Hon).*AC_off_SR;

Hou_SR = (Hou_Hon.*AC_on_SR) + (wons - Hou_Hon).*AC_off_SR;

Mia_SR = (Mia_Hon.*AC_on_SR) + (wons - Mia_Hon).*AC_off_SR;

Min_SR = (Min_Hon.*AC_on_SR) + (wons - Min_Hon).*AC_off_SR;

NYC_SR = (NYC_Hon.*AC_on_SR) + (wons - NYC_Hon).*AC_off_SR;

Phx_SR = (Phx_Hon.*AC_on_SR) + (wons - Phx_Hon).*AC_off_SR;

Riv_SR = (Riv_Hon.*AC_on_SR) + (wons - Riv_Hon).*AC_off_SR;

Wsh_SR = (Wsh_Hon.*AC_on_SR) + (wons - Wsh_Hon).*AC_off_SR;

A = [Atl_SR Aus_SR Buf_SR Chi_SR Cin_SR Hou_SR Mia_SR Min_SR NYC_SR
Phx_SR Riv_SR Wsh_SR];
Surface_Loss = A;

datasum=prctile(Surface_Loss,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Surface Loss.xlsx';
xlswrite(filename, datasum);

% Homogeneous Reactions --> Derived from CO3B-Calc Model
% average terpene concentrations and reaction rates pulled from the
```

```
% literature (multiple sources)
%                 avg conc.  avg. rxn rate with ozone
% alpha-pinene... 2.7ppb     0.0076 ppb-1 hr-1
% beta-pinene.... 0.6ppb     0.0014 ppb-1 hr-1
% d-limonene..... 3.6ppb     0.0180 ppb-1 hr-1
% styrene........ 0.4ppb     0.0015 ppb-1 hr-1
% linalool....... 0.2ppb     0.0400 ppb-1 hr-1
% alpha-terpeniol 0.4ppb     0.0270 ppb-1 hr-1

% assume a normal concentration and stdev of 0.01/hr

pd = makedist('Normal', 'mu', 0.1069, 'sigma', 0.01);
t = truncate(pd,0,1);
Y = random(t, 100000, 1);
bulkair_rxns = Y;

% Indoor ozone - AcC filter

Atl_Cin_AcC = (P.*Atl_Inf.*Atl_O3)./((Atl_Inf + Atl_Hon.*Recirc.*(wons-
fO3))+Atl_SR+bulkair_rxns);

Aus_Cin_AcC = (P.*Aus_Inf.*Aus_O3)./((Aus_Inf + Aus_Hon.*Recirc.*(wons-
fO3))+Aus_SR+bulkair_rxns);

Buf_Cin_AcC = (P.*Buf_Inf.*Buf_O3)./((Buf_Inf + Buf_Hon.*Recirc.*(wons-
fO3))+Buf_SR+bulkair_rxns);

Chi_Cin_AcC = (P.*Chi_Inf.*Chi_O3)./((Chi_Inf + Chi_Hon.*Recirc.*(wons-
fO3))+Chi_SR+bulkair_rxns);

Cin_Cin_AcC = (P.*Cin_Inf.*Cin_O3)./((Cin_Inf + Cin_Hon.*Recirc.*(wons-
fO3))+Cin_SR+bulkair_rxns);

Hou_Cin_AcC = (P.*Hou_Inf.*Hou_O3)./((Hou_Inf + Hou_Hon.*Recirc.*(wons-
fO3))+Hou_SR+bulkair_rxns);

Mia_Cin_AcC = (P.*Mia_Inf.*Mia_O3)./((Mia_Inf + Mia_Hon.*Recirc.*(wons-
fO3))+Mia_SR+bulkair_rxns);

Min_Cin_AcC = (P.*Min_Inf.*Min_O3)./((Min_Inf + Min_Hon.*Recirc.*(wons-
fO3))+Min_SR+bulkair_rxns);

NYC_Cin_AcC = (P.*NYC_Inf.*NYC_O3)./((NYC_Inf + NYC_Hon.*Recirc.*(wons-
fO3))+NYC_SR+bulkair_rxns);

Phx_Cin_AcC = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf + Phx_Hon.*Recirc.*(wons-
fO3))+Phx_SR+bulkair_rxns);

Riv_Cin_AcC = (P.*Riv_Inf.*Riv_O3)./((Riv_Inf + Riv_Hon.*Recirc.*(wons-
fO3))+Riv_SR+bulkair_rxns);
```

```
Wsh_Cin_AcC = (P.*Wsh_Inf.*Wsh_O3)./((Wsh_Inf + Wsh_Hon.*Recirc.*(wons-
fO3))+Wsh_SR+bulkair_rxns);

% Indoor ozone - No AcC filter

Atl_Cin_NoAcC = (P.*Atl_Inf.*Atl_O3)./(Atl_Inf+Atl_SR+bulkair_rxns);

Aus_Cin_NoAcC = (P.*Aus_Inf.*Aus_O3)./(Aus_Inf+Aus_SR+bulkair_rxns);

Buf_Cin_NoAcC = (P.*Buf_Inf.*Buf_O3)./(Buf_Inf+Buf_SR+bulkair_rxns);

Chi_Cin_NoAcC = (P.*Chi_Inf.*Chi_O3)./(Chi_Inf+Chi_SR+bulkair_rxns);

Cin_Cin_NoAcC = (P.*Cin_Inf.*Cin_O3)./(Cin_Inf+Cin_SR+bulkair_rxns);

Hou_Cin_NoAcC = (P.*Hou_Inf.*Hou_O3)./(Hou_Inf+Hou_SR+bulkair_rxns);

Mia_Cin_NoAcC = (P.*Mia_Inf.*Mia_O3)./(Mia_Inf+Mia_SR+bulkair_rxns);

Min_Cin_NoAcC = (P.*Min_Inf.*Min_O3)./(Min_Inf+Min_SR+bulkair_rxns);

NYC_Cin_NoAcC = (P.*NYC_Inf.*NYC_O3)./(NYC_Inf+NYC_SR+bulkair_rxns);

Phx_Cin_NoAcC = (P.*Phx_Inf.*Phx_O3)./(Phx_Inf+Phx_SR+bulkair_rxns);

Riv_Cin_NoAcC = (P.*Riv_Inf.*Riv_O3)./(Riv_Inf+Riv_SR+bulkair_rxns);

Wsh_Cin_NoAcC = (P.*Wsh_Inf.*Wsh_O3)./(Wsh_Inf+Wsh_SR+bulkair_rxns);

% Delta indoor ozone (NoAcc - AcC)

Atl_Cin = Atl_Cin_NoAcC - Atl_Cin_AcC;

Aus_Cin = Aus_Cin_NoAcC - Aus_Cin_AcC;

Buf_Cin = Buf_Cin_NoAcC - Buf_Cin_AcC;

Chi_Cin = Chi_Cin_NoAcC - Chi_Cin_AcC;

Cin_Cin = Cin_Cin_NoAcC - Cin_Cin_AcC;

Hou_Cin = Hou_Cin_NoAcC - Hou_Cin_AcC;

Mia_Cin = Mia_Cin_NoAcC - Mia_Cin_AcC;
```

```
Min_Cin = Min_Cin_NoAcC - Min_Cin_AcC;

NYC_Cin = NYC_Cin_NoAcC - NYC_Cin_AcC;

Phx_Cin = Phx_Cin_NoAcC - Phx_Cin_AcC;

Riv_Cin = Riv_Cin_NoAcC - Riv_Cin_AcC;

Wsh_Cin = Wsh_Cin_NoAcC - Wsh_Cin_AcC;

A = [Atl_Cin Aus_Cin Buf_Cin Chi_Cin Cin_Cin Hou_Cin Mia_Cin Min_Cin
NYC_Cin Phx_Cin Riv_Cin Wsh_Cin];
Delta_Cin = A;

datasum=prctile(Delta_Cin,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Delta_Cin.xlsx';
xlswrite(filename, datasum);

H=boxplot(Delta_Cin,'width',.5,'PlotStyle','compact','boxstyle',
'outline','symbol','o','medianstyle','line','colors','k','labels',{'Atl
','Aus','Buf','Chi','Cin','Hou','Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')
ylabel('Delta Ozone Concentration (ppb)', 'FontSize',
16,'fontweight','bold','FontName','Times New Roman')
saveas(gcf,'Delta Ozone.fig')

filename ='Delta_Cin_all.xlsx';
xlswrite(filename, Delta_Cin);

% Ozone Removal Effectiveness

Atl_Rem = wons - Atl_Cin_AcC./Atl_Cin_NoAcC;

Aus_Rem = wons - Aus_Cin_AcC./Aus_Cin_NoAcC;

Buf_Rem = wons - Buf_Cin_AcC./Buf_Cin_NoAcC;

Chi_Rem = wons - Chi_Cin_AcC./Chi_Cin_NoAcC;

Cin_Rem = wons - Cin_Cin_AcC./Cin_Cin_NoAcC;

Hou_Rem = wons - Hou_Cin_AcC./Hou_Cin_NoAcC;

Mia_Rem = wons - Mia_Cin_AcC./Mia_Cin_NoAcC;
```

```
Min_Rem = wons - Min_Cin_AcC./Min_Cin_NoAcC;

NYC_Rem = wons - NYC_Cin_AcC./NYC_Cin_NoAcC;

Phx_Rem = wons - Phx_Cin_AcC./Phx_Cin_NoAcC;

Riv_Rem = wons - Riv_Cin_AcC./Riv_Cin_NoAcC;

Wsh_Rem = wons - Wsh_Cin_AcC./Wsh_Cin_NoAcC;

A = [Atl_Rem Aus_Rem Buf_Rem Chi_Rem Cin_Rem Hou_Rem Mia_Rem Min_Rem
NYC_Rem Phx_Rem Riv_Rem Wsh_Rem];
Rem_Eff = A;
Rem_Eff = 100.*Rem_Eff;

datasum=prctile(Rem_Eff,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Rem_Eff.xlsx';
xlswrite(filename, datasum);

H=boxplot(Rem_Eff,'width',.5,'PlotStyle','traditional','boxstyle',
'outline','symbol','','medianstyle','line','colors','k','labels',{'Atl'
,'Aus','Buf','Chi','Cin','Hou','Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')
ylabel('Ozone Removal Effectiveness (%)', 'FontSize',
16,'fontweight','bold','FontName','Times New Roman')
saveas(gcf,'Removal Effectiveness.fig')

filename ='Rem_Eff_all.xlsx';
xlswrite(filename, Rem_Eff);


% Time In - Estimated from Klepeis et al. (2001) - estimated sigma as
0.1

pd = makedist('Normal', 'mu', .7, 'sigma', .1);
t = truncate(pd, 0,1);
Y = random(t, 100000, 1);
TimeIn = Y;

% Exposure period during summer ozone season -> May through September

O3_season = 5/12;
```

```
% DALYs and Benefits calculations

% Willingness to pay distribution from Bobinac et al. (2014) Journal of
% Pharmaeconomics

pd = makedist('Normal','mu',140000,'sigma',280000);       %Estimated
distribution from Bobinac et al. (2014)
t = truncate(pd, 0, 20000000);
Y = random(t, 100000,1);
Y = 0.5.*Y;                                                %Adjustment
factor to bring large sampling distribution back to original mean
WTP_DALY = Y;                                              %because the
truncate and random functions oversampled higher values in the
distribution

% DALYs distributions derived from city-specific age distributions in
% CO3B-Calc model for 1 ppb of ozone exposure for one year
% 1.16 is an adjustment factor for all of the distributions

Atlanta_DALY=normrnd(43.54, 18.07, 100000, 1);
%Distribution
Atlanta_DALY=Atlanta_DALY./1.16;                            %Adjustment
- distributions from 1.16 ppb ozone in CO3B-Calc
Atl_AcC_DALYs = Atlanta_DALY.* Atl_Cin.*TimeIn.*O3_season; %DALYs * Cin
* TimeIn * seasonal adjustment
Atlanta_Mort=normrnd(3.19,7.57, 100000, 1);                 %Same
process for estimated mortalities
Atlanta_Mort=Atlanta_Mort./1.16;
Atl_AcC_Morts = Atlanta_Mort.* Atl_Cin.*TimeIn.*O3_season;
Atlanta_Benefit=Atl_AcC_DALYs.*WTP_DALY;                    %#DALYs
avoided * value of an avoided DALY


Austin_DALY=normrnd(37.68, 16.11, 100000, 1);
Austin_DALY=Austin_DALY./1.16;
Aus_AcC_DALYs = Austin_DALY.* Aus_Cin.*TimeIn.*O3_season;
Austin_Mort=normrnd(2.54,6.39, 100000, 1);
Austin_Mort=Austin_Mort./1.16;
Aus_AcC_Morts = Austin_Mort.* Aus_Cin.*TimeIn.*O3_season;
Austin_Benefit=Aus_AcC_DALYs.*WTP_DALY;


Buffalo_DALY=normrnd(48.87,19.85, 100000, 1);
Buffalo_DALY=Buffalo_DALY./1.16;
Buf_AcC_DALYs = Buffalo_DALY.* Buf_Cin.*TimeIn.*O3_season;
Buffalo_Mort=normrnd(3.71,8.91, 100000, 1);
Buffalo_Mort=Buffalo_Mort./1.16;
Buf_AcC_Morts = Buffalo_Mort.* Buf_Cin.*TimeIn.*O3_season;
Buffalo_Benefit=Buf_AcC_DALYs.*WTP_DALY;
```

```
Chicago_DALY=normrnd(45.89,18.86, 100000, 1);
Chicago_DALY=Chicago_DALY./1.16;
Chi_AcC_DALYs = Chicago_DALY.* Chi_Cin.*TimeIn.*O3_season;
Chicago_Mort=normrnd(3.47,8.06, 100000, 1);
Chicago_Mort=Chicago_Mort./1.16;
Chi_AcC_Morts = Chicago_Mort.* Chi_Cin.*TimeIn.*O3_season;
Chicago_Benefit=Chi_AcC_DALYs.*WTP_DALY;


Cincinnati_DALY=normrnd(48.52,19.74, 100000, 1);
Cincinnati_DALY=Cincinnati_DALY./1.16;
Cin_AcC_DALYs = Cincinnati_DALY.*Cin_Cin.*TimeIn.*O3_season;
Cincinnati_Mort=normrnd(3.86,8.70, 100000, 1);
Cincinnati_Mort=Cincinnati_Mort./1.16;
Cin_AcC_Morts = Cincinnati_Mort.*Cin_Cin.*TimeIn.*O3_season;
Cincinnati_Benefit=Cin_AcC_DALYs.*WTP_DALY;


Houston_DALY=normrnd(38.52,16.38, 100000, 1);
Houston_DALY=Houston_DALY./1.16;
Hou_AcC_DALYs = Houston_DALY.*Hou_Cin.*TimeIn.*O3_season;
Houston_Mort=normrnd(2.63,6.54, 100000, 1);
Houston_Mort=Houston_Mort./1.16;
Hou_AcC_Morts = Houston_Mort.*Hou_Cin.*TimeIn.*O3_season;
Houston_Benefit=Hou_AcC_DALYs.*WTP_DALY;


Miami_DALY=normrnd(53.90,21.55, 100000, 1);
Miami_DALY=Miami_DALY./1.16;
Mia_AcC_DALYs = Miami_DALY.*Mia_Cin.*TimeIn.*O3_season;
Miami_Mort=normrnd(4.27,9.92, 100000, 1);
Miami_Mort=Miami_Mort./1.16;
Mia_AcC_Morts = Miami_Mort.*Mia_Cin.*TimeIn.*O3_season;
Miami_Benefit=Mia_AcC_DALYs.*WTP_DALY;


Minneapolis_DALY=normrnd(41.04,17.23, 100000, 1);
Minneapolis_DALY=Minneapolis_DALY./1.16;
Min_AcC_DALYs = Minneapolis_DALY.*Min_Cin.*TimeIn.*O3_season;
Minneapolis_Mort=normrnd(3.19,6.99, 100000, 1);
Minneapolis_Mort=Minneapolis_Mort./1.16;
Min_AcC_Morts = Minneapolis_Mort.*Min_Cin.*TimeIn.*O3_season;
Minneapolis_Benefit = Min_AcC_DALYs.*WTP_DALY;


NYC_DALY=normrnd(49.80, 20.17, 100000, 1);
NYC_DALY=NYC_DALY./1.16;
NYC_AcC_DALYs = NYC_DALY.*NYC_Cin.*TimeIn.*O3_season;
NYC_Mort=normrnd(3.84, 8.97, 100000, 1);
NYC_Mort=NYC_Mort./1.16;
NYC_AcC_Morts = NYC_Mort.*NYC_Cin.*TimeIn.*O3_season;
```

```
NYC_Benefit = NYC_AcC_DALYs.*WTP_DALY;


Phoenix_DALY=normrnd(40.37,17.00, 100000, 1);
Phoenix_DALY=Phoenix_DALY./1.16;
Phx_AcC_DALYs = Phoenix_DALY.*Phx_Cin.*TimeIn.*O3_season;
Phoenix_Mort=normrnd(2.75, 6.99, 100000, 1);
Phoenix_Mort=Phoenix_Mort./1.16;
Phx_AcC_Morts = Phoenix_Mort.*Phx_Cin.*TimeIn.*O3_season;
Phoenix_Benefit = Phx_AcC_DALYs.*WTP_DALY;


Riverside_DALY=normrnd(38.98, 16.52, 100000, 1);
Riverside_DALY=Riverside_DALY./1.16;
Riv_AcC_DALYs = Riverside_DALY.*Riv_Cin.*TimeIn.*O3_season;
Riverside_Mort=normrnd(2.74, 6.65, 100000, 1);
Riverside_Mort=Riverside_Mort./1.16;
Riv_AcC_Morts = Riverside_Mort.*Riv_Cin.*TimeIn.*O3_season;
Riverside_Benefit = Riv_AcC_DALYs.*WTP_DALY;


Washington_DALY=normrnd(48.11,19.61, 100000, 1);
Washington_DALY=Washington_DALY./1.16;
Wsh_AcC_DALYs = Washington_DALY.*Wsh_Cin.*TimeIn.*O3_season;
Washington_Mort=normrnd(3.69,8.59, 100000, 1);
Washington_Mort=Washington_Mort./1.16;
Wsh_AcC_Morts = Washington_Mort.*Wsh_Cin.*TimeIn.*O3_season;
Washington_Benefit = Wsh_AcC_DALYs.*WTP_DALY;

%DALYs

A = [Atl_AcC_DALYs Aus_AcC_DALYs Buf_AcC_DALYs Chi_AcC_DALYs
Cin_AcC_DALYs Hou_AcC_DALYs Mia_AcC_DALYs Min_AcC_DALYs NYC_AcC_DALYs
Phx_AcC_DALYs Riv_AcC_DALYs Wsh_AcC_DALYs];
DALYs = A;

datasum=prctile(DALYs,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='DALYs.xlsx';
xlswrite(filename, datasum);

H=boxplot(DALYs,'width',.75,'PlotStyle','traditional','symbol','','medi
anstyle','line','colors','k','labels',{'Atl','Aus','Buf','Chi','Cin','H
ou','Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')
```

```
ylabel('DALYs Gained per 100,000 People', 'FontSize',
16,'fontweight','bold','FontName','Times New Roman')

saveas(gcf,'DALYs.fig')

filename ='DALYs_all.xlsx';
xlswrite(filename, DALYs);

% Mortalities
A = [Atl_AcC_Morts Aus_AcC_Morts Buf_AcC_Morts Chi_AcC_Morts
Cin_AcC_Morts Hou_AcC_Morts Mia_AcC_Morts Min_AcC_Morts NYC_AcC_Morts
Phx_AcC_Morts Riv_AcC_Morts Wsh_AcC_Morts];
Morts = A;

datasum=prctile(Morts,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Morts.xlsx';
xlswrite(filename, datasum);

H=boxplot(Morts,'width',.75,'PlotStyle','traditional','symbol','','medi
anstyle','line','colors','k','labels',{'Atl','Aus','Buf','Chi','Cin','H
ou','Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')
ylabel('Mortalities Avoided per 100,000 People', 'FontSize',
16,'fontweight','bold','FontName','Times New Roman')

saveas(gcf,'Morts.fig')

filename ='Morts_all.xlsx';
xlswrite(filename, Morts);

% Benefits
A = [Atlanta_Benefit Austin_Benefit Buffalo_Benefit Chicago_Benefit
Cincinnati_Benefit Houston_Benefit Miami_Benefit Minneapolis_Benefit
NYC_Benefit Phoenix_Benefit Riverside_Benefit Washington_Benefit];
Benefit = A;

datasum=prctile(Benefit,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Benefit.xlsx';
xlswrite(filename, datasum);

filename ='Benefit_all.xlsx';
xlswrite(filename, Benefit);
```

```
H=boxplot(Benefit,'width',.75,'PlotStyle','compact','symbol','o','media
nstyle','line','colors','k','labels',{'Atl','Aus','Buf','Chi','Cin','Ho
u','Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')
ylabel('Benefits [$] per 100,000 People', 'FontSize',
16,'fontweight','bold','FontName','Times New Roman')

saveas(gcf,'Benefits.fig')

% Energy Calcs

% Flowrate through the filter
% Estimated 400 cfm per ton of cooling and 1-5 tons per home
% CARB Report -> Morrison et al. (2013)

pd = makedist('Uniform','Lower',680,'Upper',3400);
Y = random(pd, 100000,1);
Q_cmh = Y;

Q_cms = Q_cmh./3600;

% Delta pressure drop from ASHRAE Report
Delta_P_1 = 0.0001.*(Q_cmh).^1.6435;

% Estimate residential HVAC fan / motor efficiency from Stephens et al.
% (2010) HVAC&R Journal

pd = makedist('Uniform', 'Lower', .2, 'Upper',0.5);
t = truncate(pd, 0, 1);
Y = random(t, 100000,1);
Eff=Y;

% Time of operation during the ozone season

Hon_Atl_tot = 8760*(5/12).*Atl_Hon;

Hon_Aus_tot = 8760*(5/12).*Aus_Hon;

Hon_Buf_tot = 8760*(5/12).*Buf_Hon;

Hon_Chi_tot = 8760*(5/12).*Chi_Hon;

Hon_Cin_tot = 8760*(5/12).*Cin_Hon;

Hon_Hou_tot = 8760*(5/12).*Hou_Hon;
```

```
Hon_Mia_tot = 8760*(5/12).*Mia_Hon;

Hon_Min_tot = 8760*(5/12).*Min_Hon;

Hon_NYC_tot = 8760*(5/12).*NYC_Hon;

Hon_Phx_tot = 8760*(5/12).*Phx_Hon;

Hon_Riv_tot = 8760*(5/12).*Riv_Hon;

Hon_Wsh_tot = 8760*(5/12).*Wsh_Hon;

% Calculated additional kWh during ozone season

Pelec_Atl = (Q_cms.*Delta_P_1.*Hon_Atl_tot)./(1000.*Eff);

Pelec_Aus = Q_cms.*Delta_P_1.*Hon_Aus_tot./(1000.*Eff);

Pelec_Buf = Q_cms.*Delta_P_1.*Hon_Buf_tot./(1000.*Eff);

Pelec_Chi = Q_cms.*Delta_P_1.*Hon_Chi_tot./(1000.*Eff);

Pelec_Cin = Q_cms.*Delta_P_1.*Hon_Cin_tot./(1000.*Eff);

Pelec_Hou = Q_cms.*Delta_P_1.*Hon_Hou_tot./(1000.*Eff);

Pelec_Mia = Q_cms.*Delta_P_1.*Hon_Mia_tot./(1000.*Eff);

Pelec_Min = Q_cms.*Delta_P_1.*Hon_Min_tot./(1000.*Eff);

Pelec_NYC = Q_cms.*Delta_P_1.*Hon_NYC_tot./(1000.*Eff);

Pelec_Phx = Q_cms.*Delta_P_1.*Hon_Phx_tot./(1000.*Eff);

Pelec_Riv = Q_cms.*Delta_P_1.*Hon_Riv_tot./(1000.*Eff);

Pelec_Wsh = Q_cms.*Delta_P_1.*Hon_Wsh_tot./(1000.*Eff);

% Electricity costs for each city per kWh

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Atl = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Aus = Y;
```

```
pd = makedist('Uniform','Lower',.16,'Upper',.20);
Y = random(pd, 100000,1);
cost_kWh_Buf = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Chi = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Cin = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Hou = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Mia = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Min = Y;

pd = makedist('Uniform','Lower',.16,'Upper',.20);
Y = random(pd, 100000,1);
cost_kWh_NYC = Y;

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Phx = Y;

pd = makedist('Uniform','Lower',.14,'Upper',.18);
Y = random(pd, 100000,1);
cost_kWh_Riv = Y;

d = makedist('Uniform','Lower',.10,'Upper',.14);
Y = random(pd, 100000,1);
cost_kWh_Wsh = Y;

% Electricity costs -> kWh * $/kWh

Atl_elec_costs = Pelec_Atl.*cost_kWh_Atl;

Aus_elec_costs = Pelec_Aus.*cost_kWh_Aus;

Buf_elec_costs = Pelec_Buf.*cost_kWh_Buf;

Chi_elec_costs = Pelec_Chi.*cost_kWh_Chi;
```

```
Cin_elec_costs = Pelec_Cin.*cost_kWh_Cin;

Hou_elec_costs = Pelec_Hou.*cost_kWh_Hou;

Mia_elec_costs = Pelec_Mia.*cost_kWh_Mia;

Min_elec_costs = Pelec_Min.*cost_kWh_Min;

NYC_elec_costs = Pelec_NYC.*cost_kWh_NYC;

Phx_elec_costs = Pelec_Phx.*cost_kWh_Phx;

Riv_elec_costs = Pelec_Riv.*cost_kWh_Riv;

Wsh_elec_costs = Pelec_Wsh.*cost_kWh_Wsh;

%Filter costs

pd = makedist('Uniform','Lower',0,'Upper',20);
Y = random(pd, 100000,1);
Filter_cost = Y;

%Filter replacement -> assume 1-2 filters per ozone season

pd = makedist('Uniform','Lower',1,'Upper',2);
Y = random(pd, 100000,1);
Filter_replace = Y;

% Number of homes per 100,000 ppl -> divide 100,000 by average
occupancy
% per home

Atl_Homes_per100K=100000/2.18;
Aus_Homes_per100K=100000/2.37;
Buf_Homes_per100K=100000/2.24;
Chi_Homes_per100K=100000/2.57;
Cin_Homes_per100K=100000/2.17;
Hou_Homes_per100K=100000/2.67;
Mia_Homes_per100K=100000/2.58;
Min_Homes_per100K=100000/2.17;
NYC_Homes_per100K=100000/2.61;
Phx_Homes_per100K=100000/2.64;
Riv_Homes_per100K=100000/3.26;
Wsh_Homes_per100K=100000/2.13;

% Overall Filter Costs (OFC) -> electricity + filter costs
% assuming no additional labor costs
```

```
OFC_Atl = (Atl_elec_costs +
Filter_cost.*Filter_replace).*Atl_Homes_per100K;

OFC_Aus = (Aus_elec_costs +
Filter_cost.*Filter_replace).*Aus_Homes_per100K;

OFC_Buf = (Buf_elec_costs +
Filter_cost.*Filter_replace).*Buf_Homes_per100K;

OFC_Chi = (Chi_elec_costs +
Filter_cost.*Filter_replace).*Chi_Homes_per100K;

OFC_Cin = (Cin_elec_costs +
Filter_cost.*Filter_replace).*Cin_Homes_per100K;

OFC_Hou = (Hou_elec_costs +
Filter_cost.*Filter_replace).*Hou_Homes_per100K;

OFC_Mia = (Mia_elec_costs +
Filter_cost.*Filter_replace).*Mia_Homes_per100K;

OFC_Min = (Min_elec_costs +
Filter_cost.*Filter_replace).*Min_Homes_per100K;

OFC_NYC = (NYC_elec_costs +
Filter_cost.*Filter_replace).*NYC_Homes_per100K;

OFC_Phx = (Phx_elec_costs +
Filter_cost.*Filter_replace).*Phx_Homes_per100K;

OFC_Riv = (Riv_elec_costs +
Filter_cost.*Filter_replace).*Riv_Homes_per100K;

OFC_Wsh = (Wsh_elec_costs +
Filter_cost.*Filter_replace).*Wsh_Homes_per100K;


A = [OFC_Atl OFC_Aus OFC_Buf OFC_Chi OFC_Cin OFC_Hou OFC_Mia OFC_Min
OFC_NYC OFC_Phx OFC_Riv OFC_Wsh];
Costs = A;

datasum=prctile(Costs,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='Costs.xlsx';
xlswrite(filename, datasum);

filename ='Costs_all.xlsx';
xlswrite(filename, Costs);
```

```
H=boxplot(Costs,'width',.75,'PlotStyle','compact','symbol','o','medians
tyle','line','colors','k','labels',{'Atl','Aus','Buf','Chi','Cin','Hou'
,'Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
%set(H(7,:),'Visible','off')
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')
%ylim([-5000000 35000000])
ylabel('Costs [$] per 100,000 People', 'FontSize',
16,'fontweight','bold','FontName','Times New Roman')
saveas(gcf,'Costs.fig')


B_C_Atl = Atlanta_Benefit./OFC_Atl;

B_C_Aus = Austin_Benefit./OFC_Aus;

B_C_Buf = Buffalo_Benefit./OFC_Buf;

B_C_Chi = Chicago_Benefit./OFC_Chi;

B_C_Cin = Cincinnati_Benefit./OFC_Cin;

B_C_Hou = Houston_Benefit./OFC_Hou;

B_C_Mia = Miami_Benefit./OFC_Mia;

B_C_Min = Minneapolis_Benefit./OFC_Min;

B_C_NYC = NYC_Benefit./OFC_NYC;

B_C_Phx = Phoenix_Benefit./OFC_Phx;

B_C_Riv = Riverside_Benefit./OFC_Riv;

B_C_Wsh = Washington_Benefit./OFC_Wsh;


A = [B_C_Atl B_C_Aus B_C_Buf B_C_Chi B_C_Cin B_C_Hou B_C_Mia B_C_Min
B_C_NYC B_C_Phx B_C_Riv B_C_Wsh];
B_C = A;

datasum=prctile(B_C,[0 2.5 5 10 25 50 75 90 95 97.5 100],1);

filename ='B_C_Ratio.xlsx';
xlswrite(filename, datasum);
M = mean(B_C);
```

```
xlRange = 'M1';
xlswrite(filename, M, xlRange);

H=boxplot(B_C,'width',.5,'PlotStyle','traditional','symbol','','medians
tyle','line','colors','k','labels',{'Atl','Aus','Buf','Chi','Cin','Hou'
,'Mia','Min','NYC','Phx','Riv','Wsh'});
set(findobj(gca,'Type','text'),'FontSize',12,'fontweight','bold','FontN
ame','Times New Roman');
set(gcf,'color','w');
set(gca, 'FontSize', 12, 'fontweight','bold','FontName','Times New
Roman')


filename ='B_C_Ratio_all.xlsx';
xlswrite(filename, B_C);

cdfplot(B_C_Atl);
hold on
cdfplot(B_C_Aus);
cdfplot(B_C_Buf);
cdfplot(B_C_Chi);
cdfplot(B_C_Cin);
cdfplot(B_C_Hou);
cdfplot(B_C_Mia);
cdfplot(B_C_Min);
cdfplot(B_C_NYC);
cdfplot(B_C_Phx);
cdfplot(B_C_Riv);
cdfplot(B_C_Wsh);
hold off
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% NEW SCRIPT
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%MC code for analysis of filter removal efficiency in Phoenix AZ
%Key outputs include B/C for varying single pass removal efficiencies
%  activated carbon filters in homes
%Residential penetration factor estimated from Stephens et al. (2012)
%Environmental Science and Technology Journal

pd = makedist('Normal', 'mu', 0.79, 'sigma', 0.13);
t = truncate(pd, 0, 1);
Y = random(t, 100000, 1);
P = Y;

%Residential infiltration data estimated from Persily et al. (2010)
Indoor Air Journal

%Atlanta mu and sigma 0.48  0.25
%Austin  mu and sigma 0.42  0.25
%Buffalo mu and sigma 0.41  0.29
%Chicago mu and sigma 0.42  0.31
%Cincinn mu and sigma 0.42  0.31
%Houston mu and sigma 0.42  0.25
%Miami   mu and sigma 0.48  0.25
%Minneap mu and sigma 0.45  0.33
%NYC     mu and sigma 0.41  0.29
%Phoenix mu and sigma 0.50  0.23
%Riversi mu and sigma 0.40  0.21
%Wash DC mu and sigma 0.48  0.25


pd = makedist('Normal', 'mu', 0.50, 'sigma', 0.23);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Phx_Inf = Y;

fCO3_0 = 0;
fCO3_10 = 0.10;
fCO3_20 = 0.20;
fCO3_30 = 0.30;
fCO3_40 = 0.40;
fCO3_50 = 0.50;
fCO3_60 = 0.60;
fCO3_70 = 0.70;
fCO3_80 = 0.80;
fCO3_90 = 0.90;
fCO3_100 = 1.0;
```

```
%Summer HVAC cycling estimated from LBNL data using # AC compressor
hours


pd = makedist('Uniform','Lower',.27,'Upper',.47);
Y = random(pd, 100000,1);
Phx_Hon = Y;




% 100% fan operation option

%Atl_Hon = wons;
%Aus_Hon = wons;
%Buf_Hon = wons;
%Chi_Hon = wons;
%Cin_Hon = wons;
%Hou_Hon = wons;
%Mia_Hon = wons;
%Min_Hon = wons;
%NYC_Hon = wons;
%Phx_Hon = wons;
%Riv_Hon = wons;
%Wsh_Hon = wons;


pd = makedist('Normal', 'mu', 39, 'sigma', 19);
t = truncate(pd, 2,98);
Y = random(t, 100000, 1);
Phx_O3 = Y;


%Average Recirculation Rates - Stephens et al. (2011) Building and
Environ.

pd = makedist('Normal', 'mu', 7.6, 'sigma', 6.7);
t = truncate(pd, 4.3, 32.5);
Y = random(t, 100000,1);
Recirc = Y;
% adjustment factor since truncating oversampled higher values and
raised the mean/median
Recirc = Recirc./1.45;

%Ozone surface loss rates - Lee et al. (1999) and Sabersky et al.
(1973)
pd = makedist('Normal', 'mu', 2.8, 'sigma', 1.3);
t = truncate(pd,0,15);
Y = random(t, 100000, 1);
AC_off_SR = Y;
```

```
pd = makedist('Normal', 'mu', 5.4, 'sigma', 2.5);
% didn't have a sigma for Sabersky 1973 so estimated based on ratio
between mu and sigma from
% Lee et al. (1999)
t = truncate(pd,0,20);
Y = random(t, 100000, 1);
AC_on_SR = Y;

%City specific ozone surface loss rates
wons = ones(100000,1);

Phx_SR = (Phx_Hon.*AC_on_SR) + (wons - Phx_Hon).*AC_off_SR;


% Homogeneous Reactions --> Derived from CO3B-Calc Model
% average terpene concentrations and reaction rates pulled from the
% literature (multiple sources)
%                  avg conc.   avg. rxn rate with ozone
% alpha-pinene... 2.7ppb      0.0076 ppb-1 hr-1
% beta-pinene.... 0.6ppb      0.0014 ppb-1 hr-1
% d-limonene..... 3.6ppb      0.0180 ppb-1 hr-1
% styrene........ 0.4ppb      0.0015 ppb-1 hr-1
% linalool....... 0.2ppb      0.0400 ppb-1 hr-1
% alpha-terpeniol 0.4ppb      0.0270 ppb-1 hr-1

% assume a normal concentration and stdev of 0.01/hr

pd = makedist('Normal', 'mu', 0.1069, 'sigma', 0.01);
t = truncate(pd,0,1);
Y = random(t, 100000, 1);
bulkair_rxns = Y;

% Indoor ozone - AcC filter

Phx_Cin_AcC_0 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_0))+Phx_SR+bulkair_rxns);
Phx_Cin_AcC_10 = ((P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_10))+Phx_SR+bulkair_rxns))-Phx_Cin_AcC_0;
Phx_Cin_AcC_20 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_20))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_30 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_30))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_40 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_40))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_50 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_50))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_60 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_60))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_70 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_70))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
```

```
Phx_Cin_AcC_80 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_80))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_90 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_90))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_100 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_100))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;

% Time In - Estimated from Klepeis et al. (2001) - estimated sigma as
0.1

pd = makedist('Normal', 'mu', .7, 'sigma', .1);
t = truncate(pd, 0,1);
Y = random(t, 100000, 1);
TimeIn = Y;

% Exposure period during summer ozone season -> May through September

O3_season = 5/12;

% DALYs and Benefits calculations

% Willingness to pay distribution from Bobinac et al. (2014) Journal of
% Pharmaeconomics

pd = makedist('Normal','mu',140000,'sigma',280000);       %Estimated
distribution from Bobinac et al. (2014)
t = truncate(pd, 0, 20000000);
Y = random(t, 100000,1);
Y = 0.5.*Y;                                               %Adjustment
factor to bring large sampling distribution back to original mean
WTP_DALY = Y;                                             %because the
truncate and random functions oversampled higher values in the
distribution

% DALYs distributions derived from city-specific age distributions in
% CO3B-Calc model for 1 ppb of ozone exposure for one year
% 1.16 is an adjustment factor for all of the distributions

Phoenix_DALY=normrnd(40.37,17.00, 100000, 1);
Phoenix_DALY=Phoenix_DALY./1.16;

Phx_AcC_DALYs_0 = Phoenix_DALY.*Phx_Cin_AcC_0.*TimeIn.*O3_season;
Phx_AcC_DALYs_10 = Phoenix_DALY.*Phx_Cin_AcC_10.*TimeIn.*O3_season;
Phx_AcC_DALYs_20 = Phoenix_DALY.*Phx_Cin_AcC_20.*TimeIn.*O3_season;
Phx_AcC_DALYs_30 = Phoenix_DALY.*Phx_Cin_AcC_30.*TimeIn.*O3_season;
Phx_AcC_DALYs_40 = Phoenix_DALY.*Phx_Cin_AcC_40.*TimeIn.*O3_season;
Phx_AcC_DALYs_50 = Phoenix_DALY.*Phx_Cin_AcC_50.*TimeIn.*O3_season;
Phx_AcC_DALYs_60 = Phoenix_DALY.*Phx_Cin_AcC_60.*TimeIn.*O3_season;
Phx_AcC_DALYs_70 = Phoenix_DALY.*Phx_Cin_AcC_70.*TimeIn.*O3_season;
Phx_AcC_DALYs_80 = Phoenix_DALY.*Phx_Cin_AcC_80.*TimeIn.*O3_season;
Phx_AcC_DALYs_90 = Phoenix_DALY.*Phx_Cin_AcC_90.*TimeIn.*O3_season;
```

```
Phx_AcC_DALYs_100 = Phoenix_DALY.*Phx_Cin_AcC_100.*TimeIn.*O3_season;

Phoenix_Mort=normrnd(2.75, 6.99, 100000, 1);
Phoenix_Mort=Phoenix_Mort./1.16;

Phx_AcC_Morts_0 = Phoenix_Mort.*Phx_Cin_AcC_0.*TimeIn.*O3_season;
Phx_AcC_Morts_10 = Phoenix_Mort.*Phx_Cin_AcC_10.*TimeIn.*O3_season;
Phx_AcC_Morts_20 = Phoenix_Mort.*Phx_Cin_AcC_20.*TimeIn.*O3_season;
Phx_AcC_Morts_30 = Phoenix_Mort.*Phx_Cin_AcC_30.*TimeIn.*O3_season;
Phx_AcC_Morts_40 = Phoenix_Mort.*Phx_Cin_AcC_40.*TimeIn.*O3_season;
Phx_AcC_Morts_50 = Phoenix_Mort.*Phx_Cin_AcC_50.*TimeIn.*O3_season;
Phx_AcC_Morts_60 = Phoenix_Mort.*Phx_Cin_AcC_60.*TimeIn.*O3_season;
Phx_AcC_Morts_70 = Phoenix_Mort.*Phx_Cin_AcC_70.*TimeIn.*O3_season;
Phx_AcC_Morts_80 = Phoenix_Mort.*Phx_Cin_AcC_80.*TimeIn.*O3_season;
Phx_AcC_Morts_90 = Phoenix_Mort.*Phx_Cin_AcC_90.*TimeIn.*O3_season;
Phx_AcC_Morts_100 = Phoenix_Mort.*Phx_Cin_AcC_100.*TimeIn.*O3_season;


Phoenix_Benefit_0 = Phx_AcC_DALYs_0.*WTP_DALY;
Phoenix_Benefit_10 = Phx_AcC_DALYs_10.*WTP_DALY;
Phoenix_Benefit_20 = Phx_AcC_DALYs_20.*WTP_DALY;
Phoenix_Benefit_30 = Phx_AcC_DALYs_30.*WTP_DALY;
Phoenix_Benefit_40 = Phx_AcC_DALYs_40.*WTP_DALY;
Phoenix_Benefit_50 = Phx_AcC_DALYs_50.*WTP_DALY;
Phoenix_Benefit_60 = Phx_AcC_DALYs_60.*WTP_DALY;
Phoenix_Benefit_70 = Phx_AcC_DALYs_70.*WTP_DALY;
Phoenix_Benefit_80 = Phx_AcC_DALYs_80.*WTP_DALY;
Phoenix_Benefit_90 = Phx_AcC_DALYs_90.*WTP_DALY;
Phoenix_Benefit_100 = Phx_AcC_DALYs_100.*WTP_DALY;

cdfplot(Phoenix_Benefit_10);
hold on
cdfplot(Phoenix_Benefit_20);
cdfplot(Phoenix_Benefit_30);
cdfplot(Phoenix_Benefit_40);
cdfplot(Phoenix_Benefit_50);
cdfplot(Phoenix_Benefit_60);
cdfplot(Phoenix_Benefit_70);
cdfplot(Phoenix_Benefit_80);
cdfplot(Phoenix_Benefit_90);
cdfplot(Phoenix_Benefit_100);

hold off

saveas(gcf,'Phoenix Benefits.fig')



% Energy Calcs
```

```
% Flowrate through the filter
% Estimated 400 cfm per ton of cooling and 1-5 tons per home
% CARB Report -> Morrison et al. (2013)

pd = makedist('Uniform','Lower',680,'Upper',3400);
Y = random(pd, 100000,1);
Q_cmh = Y;

Q_cms = Q_cmh./3600;

% Delta pressure drop from ASHRAE Report
Delta_P_1 = 0.0001.*(Q_cmh).^1.6435;

% Estimate residential HVAC fan / motor efficiency from Stephens et al.
% (2010) HVAC&R Journal

pd = makedist('Uniform', 'Lower', .2, 'Upper',0.5);
t = truncate(pd, 0, 1);
Y = random(t, 100000,1);
Eff=Y;

% Time of operation during the ozone season


Hon_Phx_tot = 8760*(5/12).*Phx_Hon;



% Calculated additional kWh during ozone season

Pelec_Phx = Q_cms.*Delta_P_1.*Hon_Phx_tot./(1000.*Eff);

% Electricity costs for each city per kWh

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Phx = Y;

% Electricity costs -> kWh * $/kWh


Phx_elec_costs = Pelec_Phx.*cost_kWh_Phx;


%Filter costs

pd = makedist('Uniform','Lower',0,'Upper',20);
Y = random(pd, 100000,1);
Filter_cost = Y;
```

```
%Filter replacement -> assume 1-2 filters per ozone season

pd = makedist('Uniform','Lower',1,'Upper',2);
Y = random(pd, 100000,1);
Filter_replace = Y;

% Number of homes per 100,000 ppl -> divide 100,000 by average
occupancy
% per home

Phx_Homes_per100K=100000/2.64;


% Overall Filter Costs (OFC) -> electricity + filter costs
% assuming no additional labor costs


OFC_Phx = (Phx_elec_costs +
Filter_cost.*Filter_replace).*Phx_Homes_per100K;


B_C_Phx_0 = Phoenix_Benefit_0./OFC_Phx;
B_C_Phx_10 = Phoenix_Benefit_10./OFC_Phx;
B_C_Phx_20 = Phoenix_Benefit_20./OFC_Phx;
B_C_Phx_30 = Phoenix_Benefit_30./OFC_Phx;
B_C_Phx_40 = Phoenix_Benefit_40./OFC_Phx;
B_C_Phx_50 = Phoenix_Benefit_50./OFC_Phx;
B_C_Phx_60 = Phoenix_Benefit_60./OFC_Phx;
B_C_Phx_70 = Phoenix_Benefit_70./OFC_Phx;
B_C_Phx_80 = Phoenix_Benefit_80./OFC_Phx;
B_C_Phx_90 = Phoenix_Benefit_90./OFC_Phx;
B_C_Phx_100 = Phoenix_Benefit_100./OFC_Phx;


cdfplot(B_C_Phx_10);
hold on
cdfplot(B_C_Phx_20);
cdfplot(B_C_Phx_30);
cdfplot(B_C_Phx_40);
cdfplot(B_C_Phx_50);
cdfplot(B_C_Phx_60);
cdfplot(B_C_Phx_70);
cdfplot(B_C_Phx_80);
cdfplot(B_C_Phx_90);
cdfplot(B_C_Phx_100);

hold off

saveas(gcf,'Phoenix Filter Efficiency.fig')
```

```
%Summer HVAC cycling estimated from LBNL data using # AC compressor
hours


%pd = makedist('Uniform','Lower',.27,'Upper',.47);
%Y = random(pd, 100000,1);
Phx_Hon_Fan = 1;



% 100% fan operation option

%Atl_Hon = wons;
%Aus_Hon = wons;
%Buf_Hon = wons;
%Chi_Hon = wons;
%Cin_Hon = wons;
%Hou_Hon = wons;
%Mia_Hon = wons;
%Min_Hon = wons;
%NYC_Hon = wons;
%Phx_Hon = wons;
%Riv_Hon = wons;
%Wsh_Hon = wons;


pd = makedist('Normal', 'mu', 39, 'sigma', 19);
t = truncate(pd, 2,98);
Y = random(t, 100000, 1);
Phx_O3 = Y;

Phx_SR_fan = (wons.*AC_on_SR);


% Homogeneous Reactions --> Derived from CO3B-Calc Model
% average terpene concentrations and reaction rates pulled from the
% literature (multiple sources)
%                  avg conc.  avg. rxn rate with ozone
% alpha-pinene... 2.7ppb     0.0076 ppb-1 hr-1
% beta-pinene.... 0.6ppb     0.0014 ppb-1 hr-1
% d-limonene..... 3.6ppb     0.0180 ppb-1 hr-1
% styrene........ 0.4ppb     0.0015 ppb-1 hr-1
% linalool....... 0.2ppb     0.0400 ppb-1 hr-1
% alpha-terpeniol 0.4ppb     0.0270 ppb-1 hr-1

% assume a normal concentration and stdev of 0.01/hr
```

```
pd = makedist('Normal', 'mu', 0.1069, 'sigma', 0.01);
t = truncate(pd,0,1);
Y = random(t, 100000, 1);
bulkair_rxns = Y;

% Indoor ozone - AcC filter

Phx_Cin_AcC_0_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_0))+Phx_SR+bulkair_rxns);
Phx_Cin_AcC_10_fan = ((P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_10))+Phx_SR+bulkair_rxns))-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_20_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_20))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_30_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_30))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_40_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_40))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_50_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_50))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_60_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_60))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_70_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_70))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_80_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_80))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_90_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_90))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_100_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_100))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;


% DALYs distributions derived from city-specific age distributions in
% CO3B-Calc model for 1 ppb of ozone exposure for one year
% 1.16 is an adjustment factor for all of the distributions

Phoenix_DALY=normrnd(40.37,17.00, 100000, 1);
Phoenix_DALY=Phoenix_DALY./1.16;

Phx_AcC_DALYs_0_fan =
Phoenix_DALY.*Phx_Cin_AcC_0_fan.*TimeIn.*O3_season;
```

```
Phx_AcC_DALYs_10_fan =
Phoenix_DALY.*Phx_Cin_AcC_10_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_20_fan =
Phoenix_DALY.*Phx_Cin_AcC_20_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_30_fan =
Phoenix_DALY.*Phx_Cin_AcC_30_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_40_fan =
Phoenix_DALY.*Phx_Cin_AcC_40_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_50_fan =
Phoenix_DALY.*Phx_Cin_AcC_50_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_60_fan =
Phoenix_DALY.*Phx_Cin_AcC_60_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_70_fan =
Phoenix_DALY.*Phx_Cin_AcC_70_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_80_fan =
Phoenix_DALY.*Phx_Cin_AcC_80_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_90_fan =
Phoenix_DALY.*Phx_Cin_AcC_90_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_100_fan =
Phoenix_DALY.*Phx_Cin_AcC_100_fan.*TimeIn.*O3_season;

Phoenix_Mort=normrnd(2.75, 6.99, 100000, 1);
Phoenix_Mort=Phoenix_Mort./1.16;

Phx_AcC_Morts_0_fan =
Phoenix_Mort.*Phx_Cin_AcC_0_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_10_fan =
Phoenix_Mort.*Phx_Cin_AcC_10_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_20_fan =
Phoenix_Mort.*Phx_Cin_AcC_20_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_30_fan =
Phoenix_Mort.*Phx_Cin_AcC_30_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_40_fan =
Phoenix_Mort.*Phx_Cin_AcC_40_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_50_fan =
Phoenix_Mort.*Phx_Cin_AcC_50_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_60_fan =
Phoenix_Mort.*Phx_Cin_AcC_60_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_70_fan =
Phoenix_Mort.*Phx_Cin_AcC_70_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_80_fan =
Phoenix_Mort.*Phx_Cin_AcC_80_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_90_fan =
Phoenix_Mort.*Phx_Cin_AcC_90_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_100_fan =
Phoenix_Mort.*Phx_Cin_AcC_100_fan.*TimeIn.*O3_season;


Phoenix_Benefit_0_fan = Phx_AcC_DALYs_0_fan.*WTP_DALY;
Phoenix_Benefit_10_fan = Phx_AcC_DALYs_10_fan.*WTP_DALY;
Phoenix_Benefit_20_fan = Phx_AcC_DALYs_20_fan.*WTP_DALY;
Phoenix_Benefit_30_fan = Phx_AcC_DALYs_30_fan.*WTP_DALY;
```

```
Phoenix_Benefit_40_fan = Phx_AcC_DALYs_40_fan.*WTP_DALY;
Phoenix_Benefit_50_fan = Phx_AcC_DALYs_50_fan.*WTP_DALY;
Phoenix_Benefit_60_fan = Phx_AcC_DALYs_60_fan.*WTP_DALY;
Phoenix_Benefit_70_fan = Phx_AcC_DALYs_70_fan.*WTP_DALY;
Phoenix_Benefit_80_fan = Phx_AcC_DALYs_80_fan.*WTP_DALY;
Phoenix_Benefit_90_fan = Phx_AcC_DALYs_90_fan.*WTP_DALY;
Phoenix_Benefit_100_fan = Phx_AcC_DALYs_100_fan.*WTP_DALY;


% Energy Calcs

% Flowrate through the filter
% Estimated 400 cfm per ton of cooling and 1-5 tons per home
% CARB Report -> Morrison et al. (2013)

pd = makedist('Uniform','Lower',680,'Upper',3400);
Y = random(pd, 100000,1);
Q_cmh = Y;

Q_cms = Q_cmh./3600;

% Delta pressure drop from ASHRAE Report
Delta_P_1 = 0.0001.*(Q_cmh).^1.6435;

% Estimate residential HVAC fan / motor efficiency from Stephens et al.
% (2010) HVAC&R Journal

pd = makedist('Uniform', 'Lower', .2, 'Upper',0.5);
t = truncate(pd, 0, 1);
Y = random(t, 100000,1);
Eff=Y;

% Time of operation during the ozone season


Hon_Phx_tot_fan = 8760*(5/12).*Phx_Hon_Fan;




% Calculated additional kWh during ozone season

Pelec_Phx_fan = Q_cms.*Delta_P_1.*Hon_Phx_tot_fan./(1000.*Eff);

% Electricity costs for each city per kWh

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Phx = Y;
```

```
% Electricity costs -> kWh * $/kWh


Phx_elec_costs_fan = Pelec_Phx_fan.*cost_kWh_Phx;


%Filter costs

pd = makedist('Uniform','Lower',0,'Upper',20);
Y = random(pd, 100000,1);
Filter_cost = Y;

%Filter replacement -> assume 1-2 filters per ozone season

pd = makedist('Uniform','Lower',1,'Upper',2);
Y = random(pd, 100000,1);
Filter_replace = Y;

% Number of homes per 100,000 ppl -> divide 100,000 by average
occupancy
% per home

Phx_Homes_per100K=100000/2.64;


% Overall Filter Costs (OFC) -> electricity + filter costs
% assuming no additional labor costs


OFC_Phx_fan = (Phx_elec_costs_fan +
Filter_cost.*Filter_replace).*Phx_Homes_per100K;


B_C_Phx_0_fan = Phoenix_Benefit_0_fan./OFC_Phx_fan;
B_C_Phx_10_fan = Phoenix_Benefit_10_fan./OFC_Phx_fan;
B_C_Phx_20_fan = Phoenix_Benefit_20_fan./OFC_Phx_fan;
B_C_Phx_30_fan = Phoenix_Benefit_30_fan./OFC_Phx_fan;
B_C_Phx_40_fan = Phoenix_Benefit_40_fan./OFC_Phx_fan;
B_C_Phx_50_fan = Phoenix_Benefit_50_fan./OFC_Phx_fan;
B_C_Phx_60_fan = Phoenix_Benefit_60_fan./OFC_Phx_fan;
B_C_Phx_70_fan = Phoenix_Benefit_70_fan./OFC_Phx_fan;
B_C_Phx_80_fan = Phoenix_Benefit_80_fan./OFC_Phx_fan;
B_C_Phx_90_fan = Phoenix_Benefit_90_fan./OFC_Phx_fan;
B_C_Phx_100_fan = Phoenix_Benefit_100_fan./OFC_Phx_fan;


cdfplot(B_C_Phx_10_fan);
hold on
cdfplot(B_C_Phx_20_fan);
```

```
cdfplot(B_C_Phx_30_fan);
cdfplot(B_C_Phx_40_fan);
cdfplot(B_C_Phx_50_fan);
cdfplot(B_C_Phx_60_fan);
cdfplot(B_C_Phx_70_fan);
cdfplot(B_C_Phx_80_fan);
cdfplot(B_C_Phx_90_fan);
cdfplot(B_C_Phx_100_fan);

hold off

saveas(gcf,'Phoenix Filter Efficiency with fan.fig')
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% NEW SCRIPT
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%New script for Phoenix AZ - assuming all health benefits for ozone %
%   removal will occur during the summer ozone season
%Residential penetration factor estimated from Stephens et al. (2012)
%Environmental Science and Technology Journal

pd = makedist('Normal', 'mu', 0.79, 'sigma', 0.13);
t = truncate(pd, 0, 1);
Y = random(t, 100000, 1);
P = Y;

%Residential infiltration data estimated from Persily et al. (2010)
Indoor Air Journal

%Atlanta mu and sigma 0.48  0.25
%Austin  mu and sigma 0.42  0.25
%Buffalo mu and sigma 0.41  0.29
%Chicago mu and sigma 0.42  0.31
%Cincinn mu and sigma 0.42  0.31
%Houston mu and sigma 0.42  0.25
%Miami   mu and sigma 0.48  0.25
%Minneap mu and sigma 0.45  0.33
%NYC     mu and sigma 0.41  0.29
%Phoenix mu and sigma 0.50  0.23
%Riversi mu and sigma 0.40  0.21
%Wash DC mu and sigma 0.48  0.25


pd = makedist('Normal', 'mu', 0.50, 'sigma', 0.23);
t = truncate(pd, 0, 5);
Y = random(t, 100000, 1);
Phx_Inf = Y;

fCO3_0 = 0;
fCO3_10 = 0.10;
fCO3_20 = 0.20;
fCO3_30 = 0.30;
fCO3_40 = 0.40;
fCO3_50 = 0.50;
fCO3_60 = 0.60;
fCO3_70 = 0.70;
fCO3_80 = 0.80;
fCO3_90 = 0.90;
fCO3_100 = 1.0;
```

```
%Summer HVAC cycling estimated from LBNL data using # AC compressor
hours

pd = makedist('Uniform','Lower',.27,'Upper',.47);
Y = random(pd, 100000,1);
Phx_Hon = Y;


% 100% fan operation option

%Atl_Hon = wons;
%Aus_Hon = wons;
%Buf_Hon = wons;
%Chi_Hon = wons;
%Cin_Hon = wons;
%Hou_Hon = wons;
%Mia_Hon = wons;
%Min_Hon = wons;
%NYC_Hon = wons;
%Phx_Hon = wons;
%Riv_Hon = wons;
%Wsh_Hon = wons;


pd = makedist('Normal', 'mu', 39, 'sigma', 19);
t = truncate(pd, 2,98);
Y = random(t, 100000, 1);
Phx_O3 = Y;


%Average Recirculation Rates - Stephens et al. (2011) Building and
Environ.

pd = makedist('Normal', 'mu', 7.6, 'sigma', 6.7);
t = truncate(pd, 4.3, 32.5);
Y = random(t, 100000,1);
Recirc = Y;
% adjustment factor since truncating oversampled higher values and
raised the mean/median
Recirc = Recirc./1.45;

%Ozone surface loss rates - Lee et al. (1999) and Sabersky et al.
(1973)
pd = makedist('Normal', 'mu', 2.8, 'sigma', 1.3);
t = truncate(pd,0,15);
Y = random(t, 100000, 1);
AC_off_SR = Y;
```

```
pd = makedist('Normal', 'mu', 5.4, 'sigma', 2.5);
% didn't have a sigma for Sabersky 1973 so estimated based on ratio
between mu and sigma from
% Lee et al. (1999)
t = truncate(pd,0,20);
Y = random(t, 100000, 1);
AC_on_SR = Y;

%City specific ozone surface loss rates
wons = ones(100000,1);

Phx_SR = (Phx_Hon.*AC_on_SR) + (wons - Phx_Hon).*AC_off_SR;


% Homogeneous Reactions --> Derived from CO3B-Calc Model
% average terpene concentrations and reaction rates pulled from the
% literature (multiple sources)
%                  avg conc.  avg. rxn rate with ozone
% alpha-pinene... 2.7ppb     0.0076 ppb-1 hr-1
% beta-pinene.... 0.6ppb     0.0014 ppb-1 hr-1
% d-limonene..... 3.6ppb     0.0180 ppb-1 hr-1
% styrene........ 0.4ppb     0.0015 ppb-1 hr-1
% linalool....... 0.2ppb     0.0400 ppb-1 hr-1
% alpha-terpeniol 0.4ppb     0.0270 ppb-1 hr-1

% assume a normal concentration and stdev of 0.01/hr

pd = makedist('Normal', 'mu', 0.1069, 'sigma', 0.01);
t = truncate(pd,0,1);
Y = random(t, 100000, 1);
bulkair_rxns = Y;

% Indoor ozone - AcC filter

Phx_Cin_AcC_0 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_0))+Phx_SR+bulkair_rxns);
Phx_Cin_AcC_10 = ((P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_10))+Phx_SR+bulkair_rxns))-Phx_Cin_AcC_0;
Phx_Cin_AcC_20 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_20))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_30 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_30))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_40 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_40))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_50 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_50))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_60 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_60))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_70 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_70))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
```

```
Phx_Cin_AcC_80 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_80))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_90 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_90))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;
Phx_Cin_AcC_100 = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon.*Recirc.*(wons-fCO3_100))+Phx_SR+bulkair_rxns)-Phx_Cin_AcC_0;

% Time In - Estimated from Klepeis et al. (2001) - estimated sigma as
0.1

pd = makedist('Normal', 'mu', .7, 'sigma', .1);
t = truncate(pd, 0,1);
Y = random(t, 100000, 1);
TimeIn = Y;

% Exposure period during summer ozone season -> May through September

O3_season = 1.0;

% DALYs and Benefits calculations

% Willingness to pay distribution from Bobinac et al. (2014) Journal of
% Pharmaeconomics

pd = makedist('Normal','mu',140000,'sigma',280000);       %Estimated
distribution from Bobinac et al. (2014)
t = truncate(pd, 0, 20000000);
Y = random(t, 100000,1);
Y = 0.5.*Y;                                                %Adjustment
factor to bring large sampling distribution back to original mean
WTP_DALY = Y;                                              %because the
truncate and random functions oversampled higher values in the
distribution

% DALYs distributions derived from city-specific age distributions in
% CO3B-Calc model for 1 ppb of ozone exposure for one year
% 1.16 is an adjustment factor for all of the distributions

Phoenix_DALY=normrnd(40.37,17.00, 100000, 1);
Phoenix_DALY=Phoenix_DALY./1.16;

Phx_AcC_DALYs_0 = Phoenix_DALY.*Phx_Cin_AcC_0.*TimeIn.*O3_season;
Phx_AcC_DALYs_10 = Phoenix_DALY.*Phx_Cin_AcC_10.*TimeIn.*O3_season;
Phx_AcC_DALYs_20 = Phoenix_DALY.*Phx_Cin_AcC_20.*TimeIn.*O3_season;
Phx_AcC_DALYs_30 = Phoenix_DALY.*Phx_Cin_AcC_30.*TimeIn.*O3_season;
Phx_AcC_DALYs_40 = Phoenix_DALY.*Phx_Cin_AcC_40.*TimeIn.*O3_season;
Phx_AcC_DALYs_50 = Phoenix_DALY.*Phx_Cin_AcC_50.*TimeIn.*O3_season;
Phx_AcC_DALYs_60 = Phoenix_DALY.*Phx_Cin_AcC_60.*TimeIn.*O3_season;
Phx_AcC_DALYs_70 = Phoenix_DALY.*Phx_Cin_AcC_70.*TimeIn.*O3_season;
Phx_AcC_DALYs_80 = Phoenix_DALY.*Phx_Cin_AcC_80.*TimeIn.*O3_season;
Phx_AcC_DALYs_90 = Phoenix_DALY.*Phx_Cin_AcC_90.*TimeIn.*O3_season;
```

```
Phx_AcC_DALYs_100 = Phoenix_DALY.*Phx_Cin_AcC_100.*TimeIn.*O3_season;

Phoenix_Mort=normrnd(2.75, 6.99, 100000, 1);
Phoenix_Mort=Phoenix_Mort./1.16;

Phx_AcC_Morts_0 = Phoenix_Mort.*Phx_Cin_AcC_0.*TimeIn.*O3_season;
Phx_AcC_Morts_10 = Phoenix_Mort.*Phx_Cin_AcC_10.*TimeIn.*O3_season;
Phx_AcC_Morts_20 = Phoenix_Mort.*Phx_Cin_AcC_20.*TimeIn.*O3_season;
Phx_AcC_Morts_30 = Phoenix_Mort.*Phx_Cin_AcC_30.*TimeIn.*O3_season;
Phx_AcC_Morts_40 = Phoenix_Mort.*Phx_Cin_AcC_40.*TimeIn.*O3_season;
Phx_AcC_Morts_50 = Phoenix_Mort.*Phx_Cin_AcC_50.*TimeIn.*O3_season;
Phx_AcC_Morts_60 = Phoenix_Mort.*Phx_Cin_AcC_60.*TimeIn.*O3_season;
Phx_AcC_Morts_70 = Phoenix_Mort.*Phx_Cin_AcC_70.*TimeIn.*O3_season;
Phx_AcC_Morts_80 = Phoenix_Mort.*Phx_Cin_AcC_80.*TimeIn.*O3_season;
Phx_AcC_Morts_90 = Phoenix_Mort.*Phx_Cin_AcC_90.*TimeIn.*O3_season;
Phx_AcC_Morts_100 = Phoenix_Mort.*Phx_Cin_AcC_100.*TimeIn.*O3_season;


Phoenix_Benefit_0 = Phx_AcC_DALYs_0.*WTP_DALY;
Phoenix_Benefit_10 = Phx_AcC_DALYs_10.*WTP_DALY;
Phoenix_Benefit_20 = Phx_AcC_DALYs_20.*WTP_DALY;
Phoenix_Benefit_30 = Phx_AcC_DALYs_30.*WTP_DALY;
Phoenix_Benefit_40 = Phx_AcC_DALYs_40.*WTP_DALY;
Phoenix_Benefit_50 = Phx_AcC_DALYs_50.*WTP_DALY;
Phoenix_Benefit_60 = Phx_AcC_DALYs_60.*WTP_DALY;
Phoenix_Benefit_70 = Phx_AcC_DALYs_70.*WTP_DALY;
Phoenix_Benefit_80 = Phx_AcC_DALYs_80.*WTP_DALY;
Phoenix_Benefit_90 = Phx_AcC_DALYs_90.*WTP_DALY;
Phoenix_Benefit_100 = Phx_AcC_DALYs_100.*WTP_DALY;

cdfplot(Phoenix_Benefit_10);
hold on
cdfplot(Phoenix_Benefit_20);
cdfplot(Phoenix_Benefit_30);
cdfplot(Phoenix_Benefit_40);
cdfplot(Phoenix_Benefit_50);
cdfplot(Phoenix_Benefit_60);
cdfplot(Phoenix_Benefit_70);
cdfplot(Phoenix_Benefit_80);
cdfplot(Phoenix_Benefit_90);
cdfplot(Phoenix_Benefit_100);

hold off

saveas(gcf,'Phoenix Benefits 1.0 Ozone.fig')


% Energy Calcs

% Flowrate through the filter
% Estimated 400 cfm per ton of cooling and 1-5 tons per home
```

```
% CARB Report -> Morrison et al. (2013)

pd = makedist('Uniform','Lower',680,'Upper',3400);
Y = random(pd, 100000,1);
Q_cmh = Y;

Q_cms = Q_cmh./3600;

% Delta pressure drop from ASHRAE Report
Delta_P_1 = 0.0001.*(Q_cmh).^1.6435;

% Estimate residential HVAC fan / motor efficiency from Stephens et al.
% (2010) HVAC&R Journal

pd = makedist('Uniform', 'Lower', .2, 'Upper',0.5);
t = truncate(pd, 0, 1);
Y = random(t, 100000,1);
Eff=Y;

% Time of operation during the ozone season


Hon_Phx_tot = 8760*(5/12).*Phx_Hon;



% Calculated additional kWh during ozone season

Pelec_Phx = Q_cms.*Delta_P_1.*Hon_Phx_tot./(1000.*Eff);

% Electricity costs for each city per kWh

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Phx = Y;

% Electricity costs -> kWh * $/kWh


Phx_elec_costs = Pelec_Phx.*cost_kWh_Phx;


%Filter costs

pd = makedist('Uniform','Lower',0,'Upper',20);
Y = random(pd, 100000,1);
Filter_cost = Y;
```

```
%Filter replacement -> assume 1-2 filters per ozone season

pd = makedist('Uniform','Lower',1,'Upper',2);
Y = random(pd, 100000,1);
Filter_replace = Y;

% Number of homes per 100,000 ppl -> divide 100,000 by average
occupancy
% per home

Phx_Homes_per100K=100000/2.64;


% Overall Filter Costs (OFC) -> electricity + filter costs
% assuming no additional labor costs


OFC_Phx = (Phx_elec_costs +
Filter_cost.*Filter_replace).*Phx_Homes_per100K;


B_C_Phx_0 = Phoenix_Benefit_0./OFC_Phx;
B_C_Phx_10 = Phoenix_Benefit_10./OFC_Phx;
B_C_Phx_20 = Phoenix_Benefit_20./OFC_Phx;
B_C_Phx_30 = Phoenix_Benefit_30./OFC_Phx;
B_C_Phx_40 = Phoenix_Benefit_40./OFC_Phx;
B_C_Phx_50 = Phoenix_Benefit_50./OFC_Phx;
B_C_Phx_60 = Phoenix_Benefit_60./OFC_Phx;
B_C_Phx_70 = Phoenix_Benefit_70./OFC_Phx;
B_C_Phx_80 = Phoenix_Benefit_80./OFC_Phx;
B_C_Phx_90 = Phoenix_Benefit_90./OFC_Phx;
B_C_Phx_100 = Phoenix_Benefit_100./OFC_Phx;


cdfplot(B_C_Phx_10);
hold on
cdfplot(B_C_Phx_20);
cdfplot(B_C_Phx_30);
cdfplot(B_C_Phx_40);
cdfplot(B_C_Phx_50);
cdfplot(B_C_Phx_60);
cdfplot(B_C_Phx_70);
cdfplot(B_C_Phx_80);
cdfplot(B_C_Phx_90);
cdfplot(B_C_Phx_100);

hold off

saveas(gcf,'Phoenix Filter Efficiency 1.0 Ozone.fig')
```

```
%Summer HVAC cycling estimated from LBNL data using # AC compressor
hours


%pd = makedist('Uniform','Lower',.27,'Upper',.47);
%Y = random(pd, 100000,1);
Phx_Hon_Fan = 1;



% 100% fan operation option

%Atl_Hon = wons;
%Aus_Hon = wons;
%Buf_Hon = wons;
%Chi_Hon = wons;
%Cin_Hon = wons;
%Hou_Hon = wons;
%Mia_Hon = wons;
%Min_Hon = wons;
%NYC_Hon = wons;
%Phx_Hon = wons;
%Riv_Hon = wons;
%Wsh_Hon = wons;


pd = makedist('Normal', 'mu', 39, 'sigma', 19);
t = truncate(pd, 2,98);
Y = random(t, 100000, 1);
Phx_O3 = Y;

Phx_SR_fan = (wons.*AC_on_SR);


% Homogeneous Reactions --> Derived from CO3B-Calc Model
% average terpene concentrations and reaction rates pulled from the
% literature (multiple sources)
%                avg conc.  avg. rxn rate with ozone
% alpha-pinene... 2.7ppb     0.0076 ppb-1 hr-1
% beta-pinene.... 0.6ppb     0.0014 ppb-1 hr-1
% d-limonene..... 3.6ppb     0.0180 ppb-1 hr-1
% styrene........ 0.4ppb     0.0015 ppb-1 hr-1
% linalool....... 0.2ppb     0.0400 ppb-1 hr-1
% alpha-terpeniol 0.4ppb     0.0270 ppb-1 hr-1

% assume a normal concentration and stdev of 0.01/hr

pd = makedist('Normal', 'mu', 0.1069, 'sigma', 0.01);
```

```
t = truncate(pd,0,1);
Y = random(t, 100000, 1);
bulkair_rxns = Y;

% Indoor ozone - AcC filter

Phx_Cin_AcC_0_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_0))+Phx_SR+bulkair_rxns);
Phx_Cin_AcC_10_fan = ((P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_10))+Phx_SR+bulkair_rxns))-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_20_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_20))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_30_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_30))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_40_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_40))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_50_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_50))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_60_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_60))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_70_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_70))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_80_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_80))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_90_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_90))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;
Phx_Cin_AcC_100_fan = (P.*Phx_Inf.*Phx_O3)./((Phx_Inf +
Phx_Hon_Fan.*Recirc.*(wons-fCO3_100))+Phx_SR+bulkair_rxns)-
Phx_Cin_AcC_0_fan;



% DALYs distributions derived from city-specific age distributions in
% CO3B-Calc model for 1 ppb of ozone exposure for one year
% 1.16 is an adjustment factor for all of the distributions

Phoenix_DALY=normrnd(40.37,17.00, 100000, 1);
Phoenix_DALY=Phoenix_DALY./1.16;

Phx_AcC_DALYs_0_fan =
Phoenix_DALY.*Phx_Cin_AcC_0_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_10_fan =
Phoenix_DALY.*Phx_Cin_AcC_10_fan.*TimeIn.*O3_season;
```

```
Phx_AcC_DALYs_20_fan =
Phoenix_DALY.*Phx_Cin_AcC_20_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_30_fan =
Phoenix_DALY.*Phx_Cin_AcC_30_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_40_fan =
Phoenix_DALY.*Phx_Cin_AcC_40_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_50_fan =
Phoenix_DALY.*Phx_Cin_AcC_50_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_60_fan =
Phoenix_DALY.*Phx_Cin_AcC_60_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_70_fan =
Phoenix_DALY.*Phx_Cin_AcC_70_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_80_fan =
Phoenix_DALY.*Phx_Cin_AcC_80_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_90_fan =
Phoenix_DALY.*Phx_Cin_AcC_90_fan.*TimeIn.*O3_season;
Phx_AcC_DALYs_100_fan =
Phoenix_DALY.*Phx_Cin_AcC_100_fan.*TimeIn.*O3_season;

Phoenix_Mort=normrnd(2.75, 6.99, 100000, 1);
Phoenix_Mort=Phoenix_Mort./1.16;

Phx_AcC_Morts_0_fan =
Phoenix_Mort.*Phx_Cin_AcC_0_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_10_fan =
Phoenix_Mort.*Phx_Cin_AcC_10_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_20_fan =
Phoenix_Mort.*Phx_Cin_AcC_20_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_30_fan =
Phoenix_Mort.*Phx_Cin_AcC_30_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_40_fan =
Phoenix_Mort.*Phx_Cin_AcC_40_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_50_fan =
Phoenix_Mort.*Phx_Cin_AcC_50_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_60_fan =
Phoenix_Mort.*Phx_Cin_AcC_60_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_70_fan =
Phoenix_Mort.*Phx_Cin_AcC_70_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_80_fan =
Phoenix_Mort.*Phx_Cin_AcC_80_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_90_fan =
Phoenix_Mort.*Phx_Cin_AcC_90_fan.*TimeIn.*O3_season;
Phx_AcC_Morts_100_fan =
Phoenix_Mort.*Phx_Cin_AcC_100_fan.*TimeIn.*O3_season;


Phoenix_Benefit_0_fan = Phx_AcC_DALYs_0_fan.*WTP_DALY;
Phoenix_Benefit_10_fan = Phx_AcC_DALYs_10_fan.*WTP_DALY;
Phoenix_Benefit_20_fan = Phx_AcC_DALYs_20_fan.*WTP_DALY;
Phoenix_Benefit_30_fan = Phx_AcC_DALYs_30_fan.*WTP_DALY;
Phoenix_Benefit_40_fan = Phx_AcC_DALYs_40_fan.*WTP_DALY;
Phoenix_Benefit_50_fan = Phx_AcC_DALYs_50_fan.*WTP_DALY;
```

```
Phoenix_Benefit_60_fan = Phx_AcC_DALYs_60_fan.*WTP_DALY;
Phoenix_Benefit_70_fan = Phx_AcC_DALYs_70_fan.*WTP_DALY;
Phoenix_Benefit_80_fan = Phx_AcC_DALYs_80_fan.*WTP_DALY;
Phoenix_Benefit_90_fan = Phx_AcC_DALYs_90_fan.*WTP_DALY;
Phoenix_Benefit_100_fan = Phx_AcC_DALYs_100_fan.*WTP_DALY;


% Energy Calcs

% Flowrate through the filter
% Estimated 400 cfm per ton of cooling and 1-5 tons per home
% CARB Report -> Morrison et al. (2013)

pd = makedist('Uniform','Lower',680,'Upper',3400);
Y = random(pd, 100000,1);
Q_cmh = Y;

Q_cms = Q_cmh./3600;

% Delta pressure drop from ASHRAE Report
Delta_P_1 = 0.0001.*(Q_cmh).^1.6435;

% Estimate residential HVAC fan / motor efficiency from Stephens et al.
% (2010) HVAC&R Journal

pd = makedist('Uniform', 'Lower', .2, 'Upper',0.5);
t = truncate(pd, 0, 1);
Y = random(t, 100000,1);
Eff=Y;

% Time of operation during the ozone season


Hon_Phx_tot_fan = 8760*(5/12).*Phx_Hon_Fan;



% Calculated additional kWh during ozone season

Pelec_Phx_fan = Q_cms.*Delta_P_1.*Hon_Phx_tot_fan./(1000.*Eff);

% Electricity costs for each city per kWh

pd = makedist('Uniform','Lower',.09,'Upper',.13);
Y = random(pd, 100000,1);
cost_kWh_Phx = Y;

% Electricity costs -> kWh * $/kWh
```

```
Phx_elec_costs_fan = Pelec_Phx_fan.*cost_kWh_Phx;


%Filter costs

pd = makedist('Uniform','Lower',0,'Upper',20);
Y = random(pd, 100000,1);
Filter_cost = Y;

%Filter replacement -> assume 1-2 filters per ozone season

pd = makedist('Uniform','Lower',1,'Upper',2);
Y = random(pd, 100000,1);
Filter_replace = Y;

% Number of homes per 100,000 ppl -> divide 100,000 by average
occupancy
% per home

Phx_Homes_per100K=100000/2.64;


% Overall Filter Costs (OFC) -> electricity + filter costs
% assuming no additional labor costs


OFC_Phx_fan = (Phx_elec_costs_fan +
Filter_cost.*Filter_replace).*Phx_Homes_per100K;


B_C_Phx_0_fan = Phoenix_Benefit_0_fan./OFC_Phx_fan;
B_C_Phx_10_fan = Phoenix_Benefit_10_fan./OFC_Phx_fan;
B_C_Phx_20_fan = Phoenix_Benefit_20_fan./OFC_Phx_fan;
B_C_Phx_30_fan = Phoenix_Benefit_30_fan./OFC_Phx_fan;
B_C_Phx_40_fan = Phoenix_Benefit_40_fan./OFC_Phx_fan;
B_C_Phx_50_fan = Phoenix_Benefit_50_fan./OFC_Phx_fan;
B_C_Phx_60_fan = Phoenix_Benefit_60_fan./OFC_Phx_fan;
B_C_Phx_70_fan = Phoenix_Benefit_70_fan./OFC_Phx_fan;
B_C_Phx_80_fan = Phoenix_Benefit_80_fan./OFC_Phx_fan;
B_C_Phx_90_fan = Phoenix_Benefit_90_fan./OFC_Phx_fan;
B_C_Phx_100_fan = Phoenix_Benefit_100_fan./OFC_Phx_fan;


cdfplot(B_C_Phx_10_fan);
hold on
cdfplot(B_C_Phx_20_fan);
cdfplot(B_C_Phx_30_fan);
cdfplot(B_C_Phx_40_fan);
```

```
cdfplot(B_C_Phx_50_fan);
cdfplot(B_C_Phx_60_fan);
cdfplot(B_C_Phx_70_fan);
cdfplot(B_C_Phx_80_fan);
cdfplot(B_C_Phx_90_fan);
cdfplot(B_C_Phx_100_fan);

hold off

saveas(gcf,'Phoenix Filter Efficiency with fan.fig')
```

Appendix E

Multivariate Linear Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Qmakeup, Ozone_out, filter_eff, dollar_kwh, A85_plus, A1_4, A55_64, A35_44, A15_24, hvac_op, A25_34, A75_84, A45_54, A65_74, A5_14[b]	.	Enter

a. Dependent Variable: B_C

b. Tolerance = .000 limit reached.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.989[a]	.978	.972	31.582

a. Predictors: (Constant), Qmakeup, Ozone_out, filter_eff, dollar_kwh, A85_plus, A1_4, A55_64, A35_44, A15_24, hvac_op, A25_34, A75_84, A45_54, A65_74, A5_14

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2318309.756	15	154553.984	154.957	.000[b]
	Residual	51864.634	52	997.397		
	Total	2370174.390	67			

a. Dependent Variable: B_C

b. Predictors: (Constant), Qmakeup, Ozone_out, filter_eff, dollar_kwh, A85_plus, A1_4, A55_64, A35_44, A15_24, hvac_op, A25_34, A75_84, A45_54, A65_74, A5_14

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	348.094	737.376		.472	.639
	Ozone_out	2.538	.750	.085	3.382	.001
	hvac_op	-50.671	72.977	-.089	-.694	.491
	dollar_kwh	37.831	156.506	.006	.242	.810
	filter_eff	57.333	62.751	.023	.914	.365
	A1_4	2285.399	1594.771	.333	1.433	.158
	A5_14	-1318.595	929.809	-2.785	-1.418	.162
	A15_24	-992.999	874.961	-.372	-1.135	.262
	A25_34	-347.967	791.664	-.236	-.440	.662
	A35_44	-844.079	793.089	-.487	-1.064	.292
	A45_54	-139.901	969.286	-.071	-.144	.886
	A55_64	-911.315	915.839	-.339	-.995	.324
	A65_74	-282.642	729.714	-.315	-.387	.700
	A75_84	850.254	804.717	.609	1.057	.296
	A85_plus	-1188.277	758.925	-.352	-1.566	.123
	Qmakeup	.021	.011	1.775	1.952	.056

a. Dependent Variable: B_C

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	occupancy	-13.238[b]	-.807	.423	-.112	1.576E-6
	dollar_daly	.[b]	.	.	.	.000

a. Dependent Variable: B_C

b. Predictors in the Model: (Constant), Qmakeup, Ozone_out, filter_eff, dollar_kwh, A85_plus, A1_4, A55_64, A35_44, A15_24, hvac_op, A25_34, A75_84, A45_54, A65_74, A5_14

Single Family Homes Simulation Run

Notes

Output Created		23-APR-2015 08:14:40
Comments		
Input	Data	/Users/joshaldred/Documents/test_22_april_2015.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	68

Simulation Summary

Maximum cases*			100000
Input filtering	Input: Ozone_out	Minimum value	>= .00
		Maximum value	<= 100.00
Cases filtered			2.3%
Sensitivity analysis iterations			2
Sensitivity analysis	Iteration 1	Simulated cases	100000
		Cases filtered	2.3%
	Iteration 2	Simulated cases	100000
		Cases filtered	2.3%
Stopping criteria achieved			Yes
Total simulated cases			200000

Simulation Plan File: /Users/joshaldred/Documents/singlefamilyhomev2.splan
Cases may be filtered because of either targets or inputs that are outside of the specified ranges. Filtered cases are not included in the simulated cases count.
*. Maximum cases is the same for each iteration.

Iterations for Sensitivity Analysis
Input Field: Qmakeup

Uniform Distribution		Parameter Value
Iteration 1	max	62.50
	min	.00
Iteration 2	max	30.00
	min	.00

	Qmakeup:max*	Mean	Std. Deviation	Median	Minimum	Maximum
B_C	62.500	28.722	37.509	27.608	-74.83	200.71
	30.000	28.452	37.429	27.270	-74.32	194.33

Descriptive Statistics of Scale Inputs

	Qmakeup:max*	Mean	Std. Deviation	Minimum	Maximum
Ozone_out	62.500	30.777	14.135	.00	96.38
	30.000	30.802	14.120	.00	93.43
Qmakeup	62.500	31.286	18.017	.00	62.50
	30.000	14.971	8.670	.00	30.00
dollar_kwh	62.500	.150	.029	.10	.20
	30.000	.151	.029	.10	.20
filter_eff	62.500	.550	.202	.20	.90
	30.000	.549	.202	.20	.90
hvac_op	62.500	.300	.087	.15	.45
	30.000	.300	.087	.15	.45

*. Iterated input field: Qmakeup. Fixed distribution parameters: min = .00. Data are regenerated for each iteration.

Correlations

Qmakeup:max=62.50*

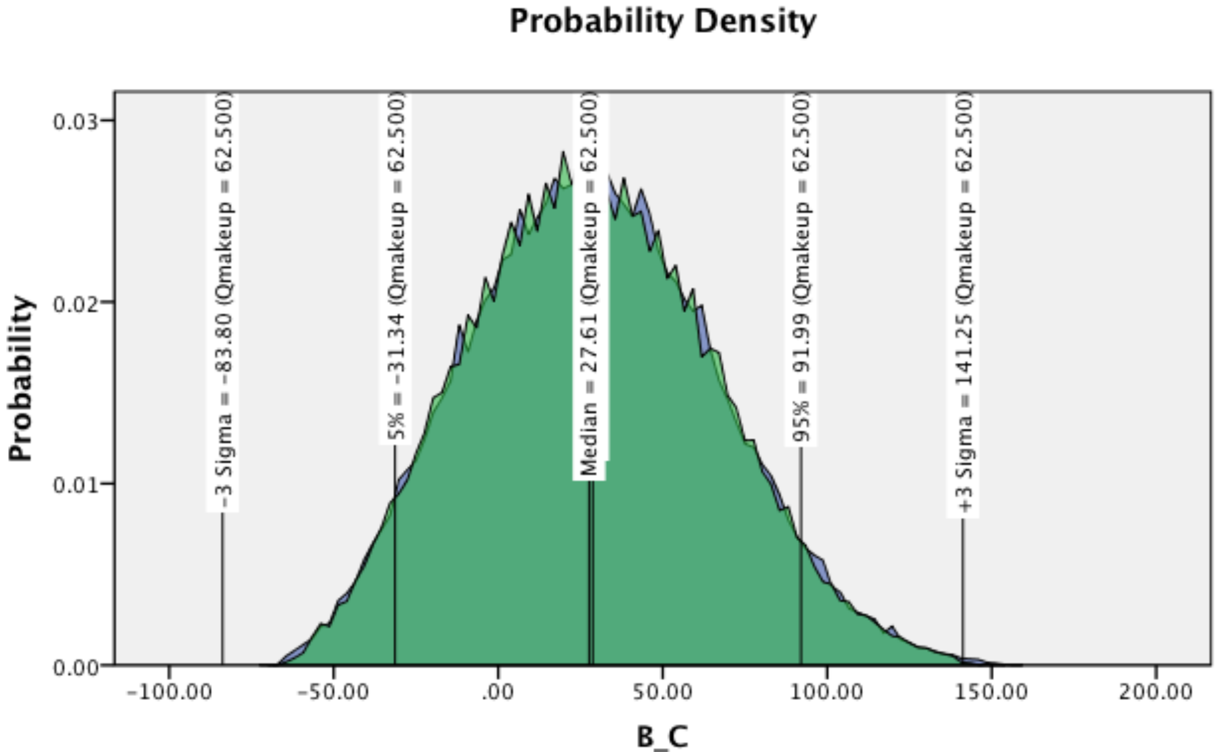
	dollar_kwh	filter_eff	hvac_op	Ozone_out	Qmakeup
dollar_kwh	1.000	-.091	-.297	.319	-.116
filter_eff	-.091	1.000	.229	-.060	-.129
hvac_op	-.297	.229	1.000	-.046	.359
Ozone_out	.319	-.060	-.046	1.000	.032
Qmakeup	-.116	-.129	.359	.032	1.000

Correlations between simulated inputs may differ from correlations specified for those inputs in the simulation plan.
Excluded fields (fixed inputs and inputs with categorical distributions): A15_24 A1_4 A25_34 A35_44 A45_54 A55_64 A5_14 A65_74 A75_84 A85_plus*
*. Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min = .00

Qmakeup:max=30.00*

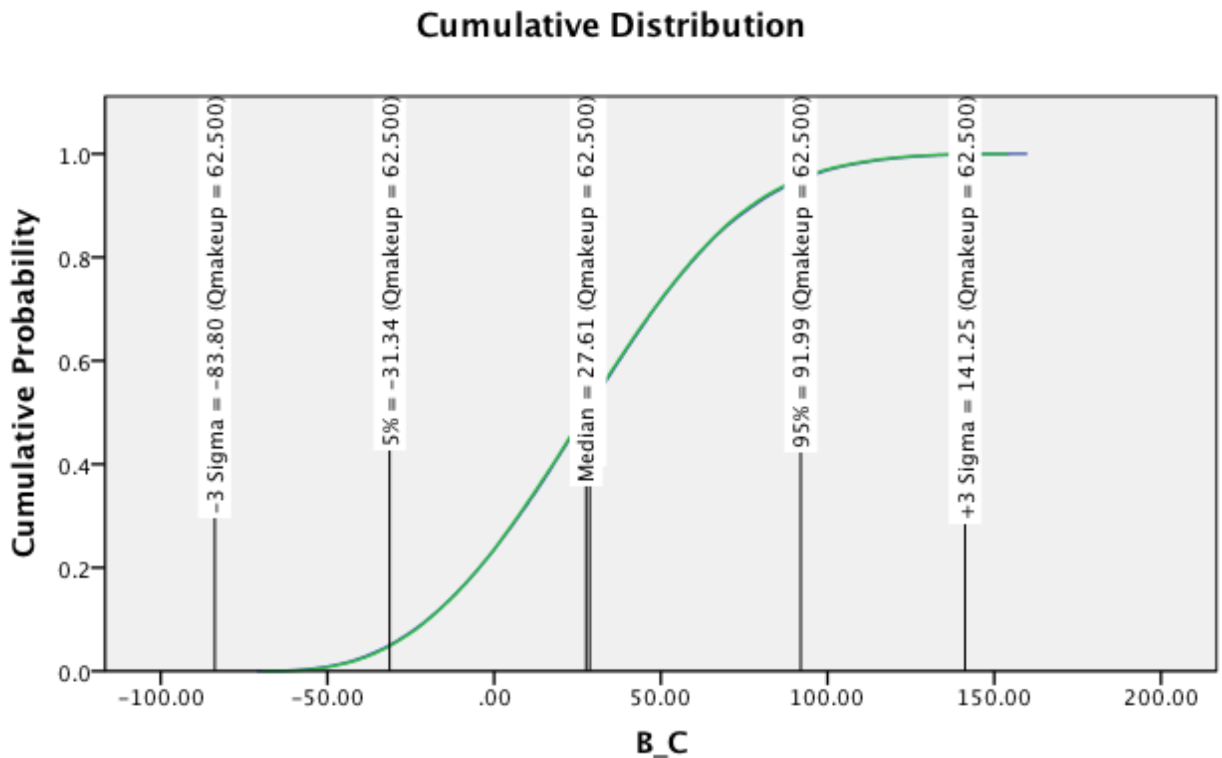
	dollar_kwh	filter_eff	hvac_op	Ozone_out	Qmakeup
dollar_kwh	1.000	-.045	-.301	.293	-.123
filter_eff	-.045	1.000	.240	-.067	-.106
hvac_op	-.301	.240	1.000	-.060	.410
Ozone_out	.293	-.067	-.060	1.000	.010
Qmakeup	-.123	-.106	.410	.010	1.000

Correlations between simulated inputs may differ from correlations specified for those inputs in the simulation plan.
Excluded fields (fixed inputs and inputs with categorical distributions): A15_24 A1_4 A25_34 A35_44 A45_54 A55_64 A5_14 A65_74 A75_84 A85_plus*
*. Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min = .00



Qmakeup: max*	< -31.34	-31.34 - 91.99	> 91.99
62.500	5%	90%	5%
30.000	5%	91%	5%

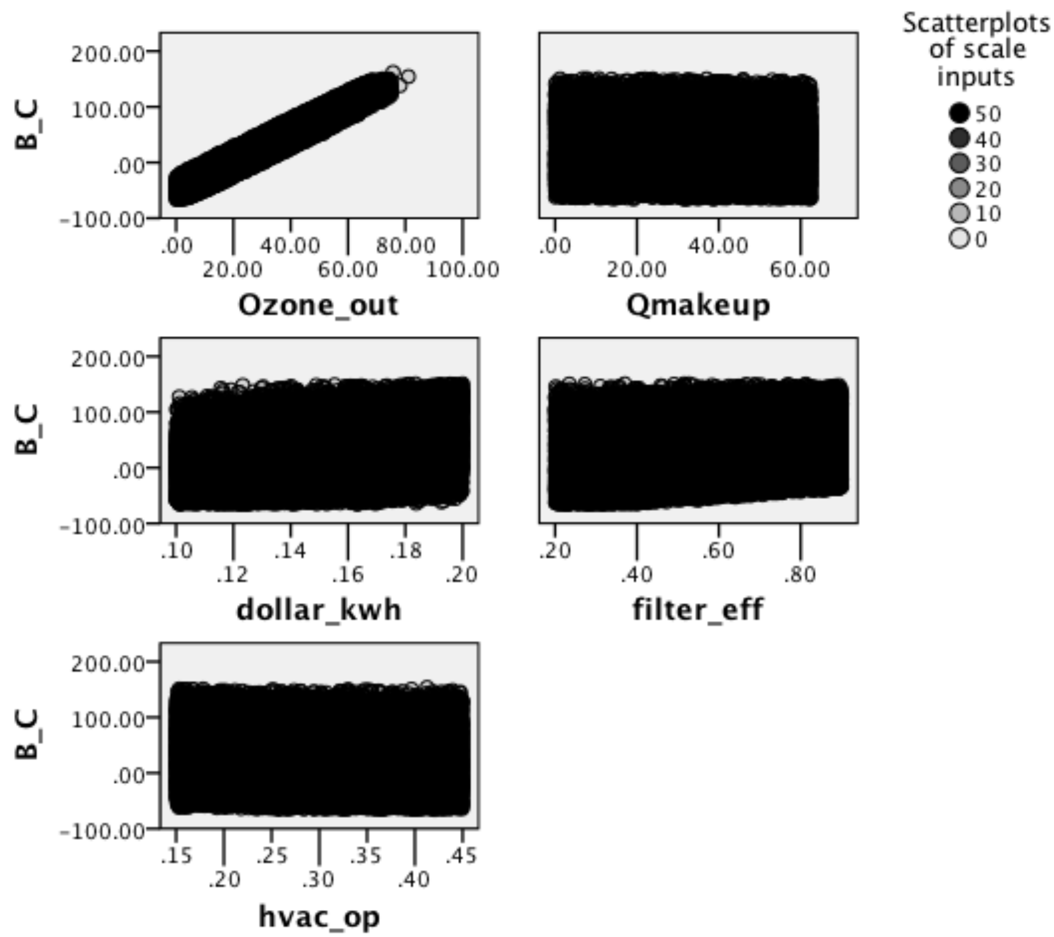
*Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min=.00

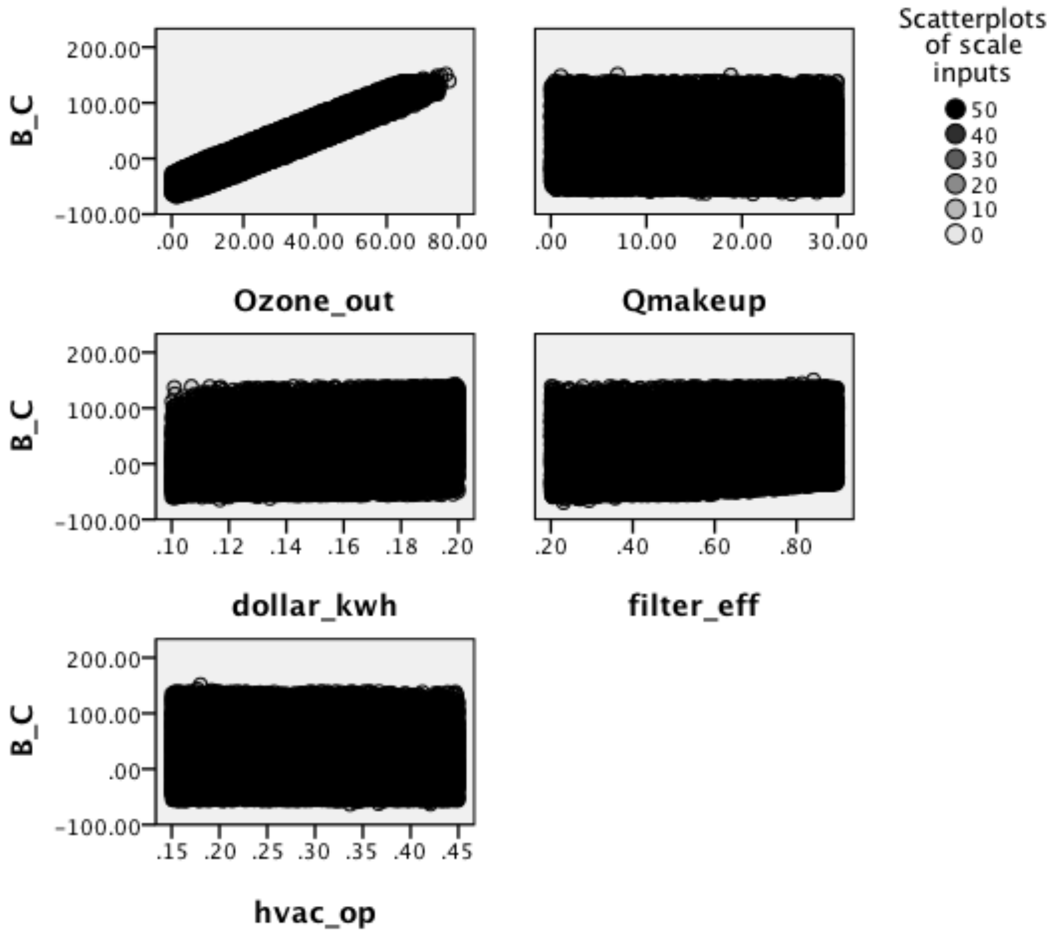


Qmakeup: max*	< -31.34	-31.34 - 91.99	> 91.99
62.500	5%	90%	5%
30.000	5%	91%	5%

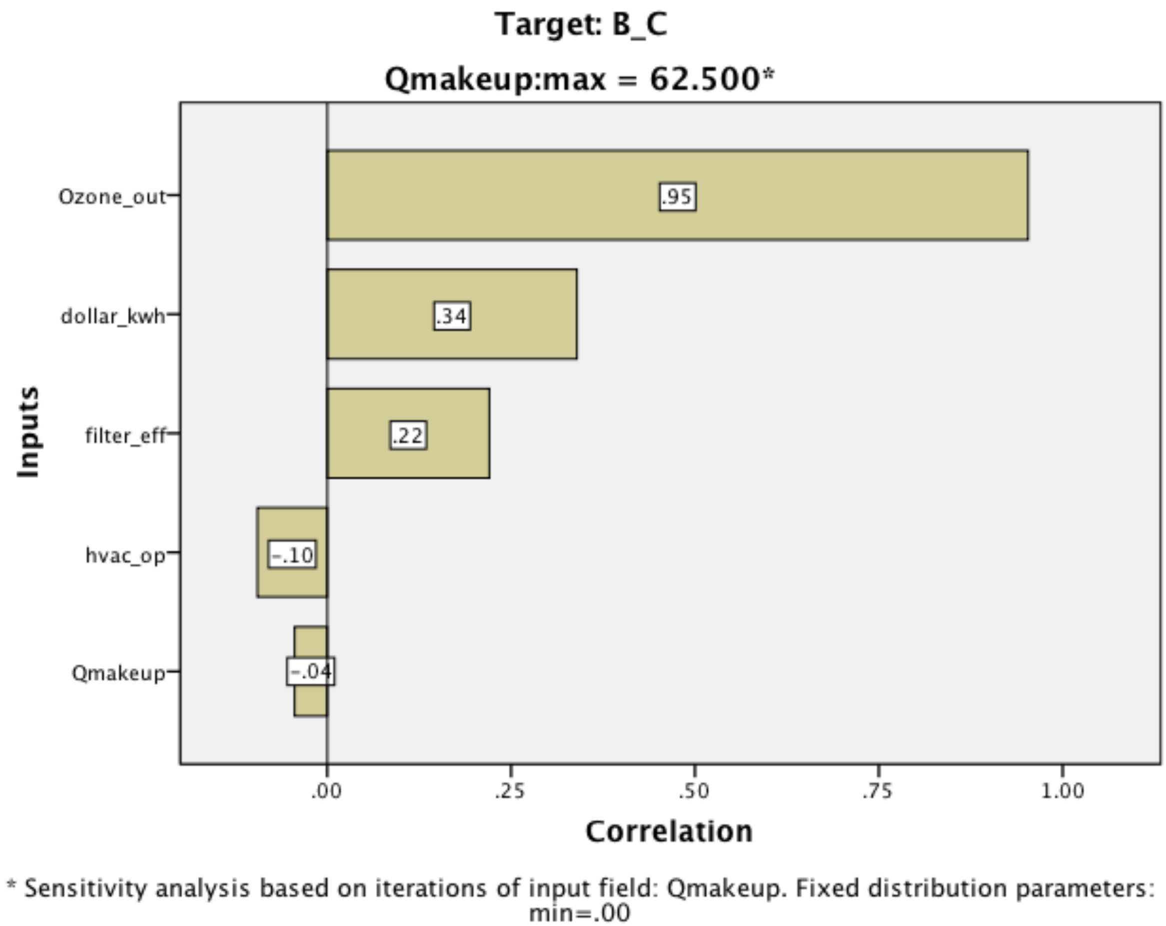
*Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min=.00

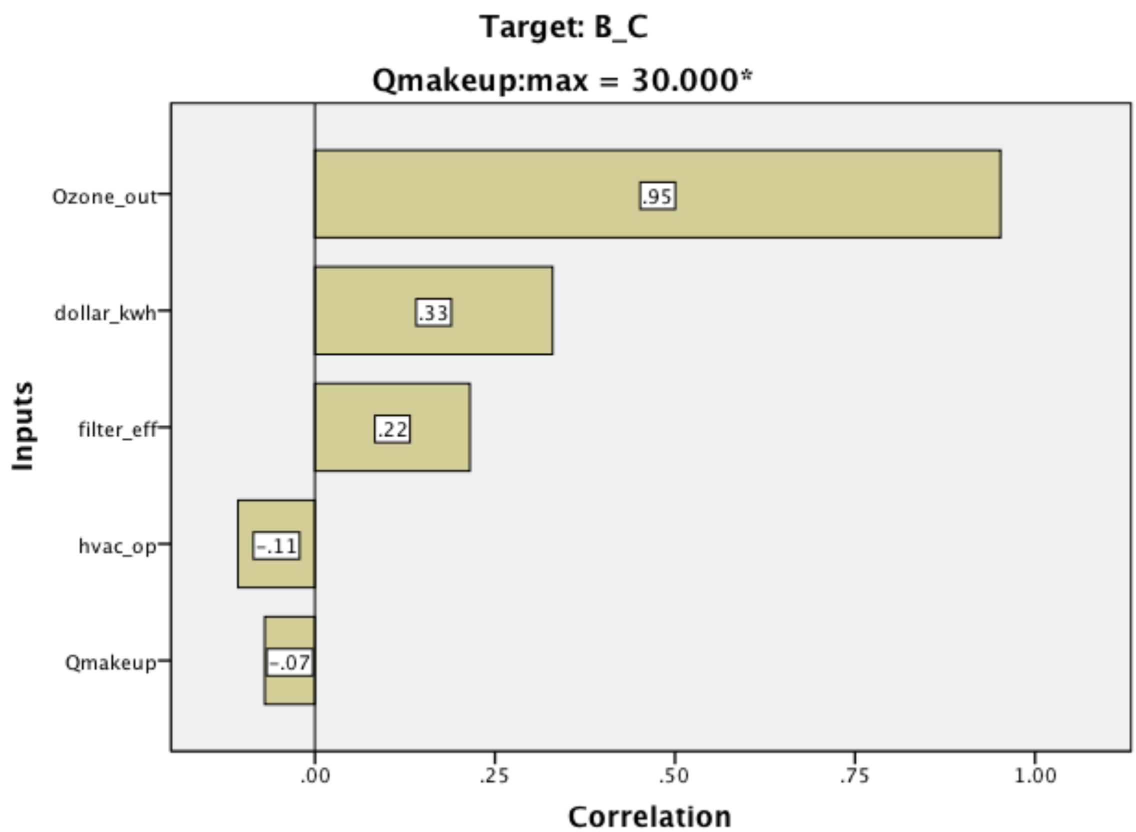
Scatterplots of scale inputs




Scatterplots of scale inputs
50
40
30
20
10
0
B_C
200.00
100.00
.00
-100.00
.00
20.00
40.00
60.00
80.00
Ozone_out
10.00
30.00
Qmakeup
.10
.12
.14
.16
.18
.20
dollar_kwh
.40
.60
.80
filter_eff
.15
.25
.30
.35
.45
hvac_op

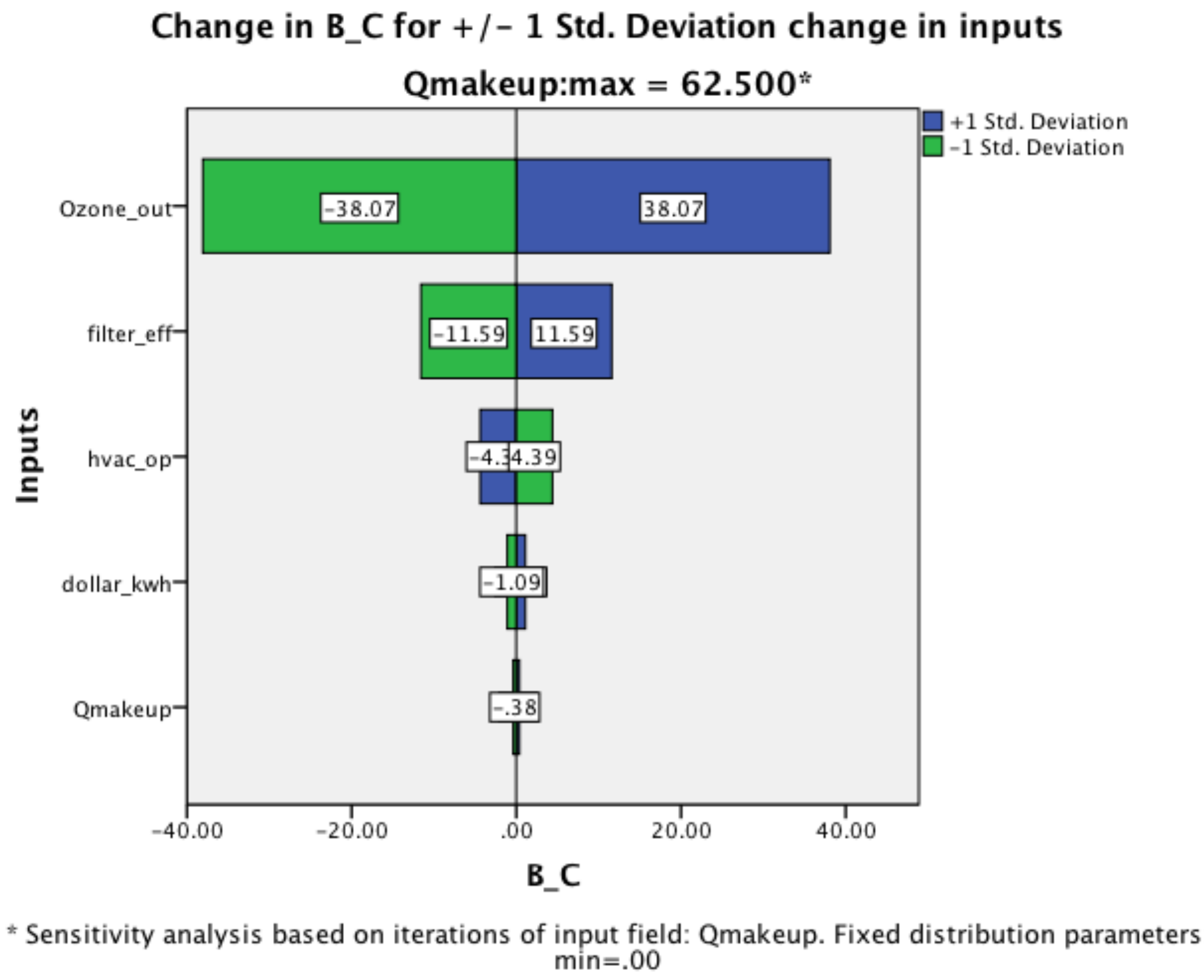
Tornado Charts

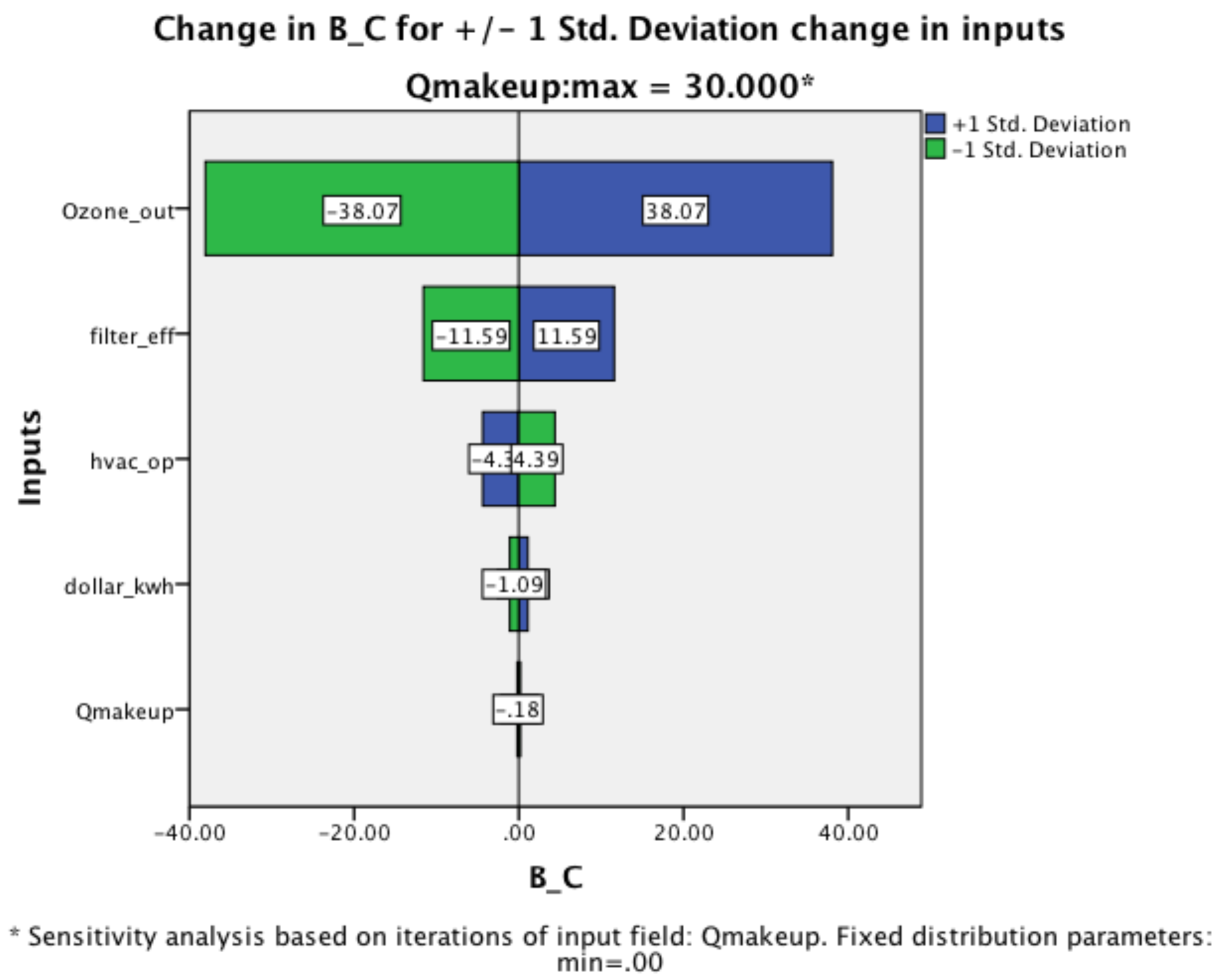




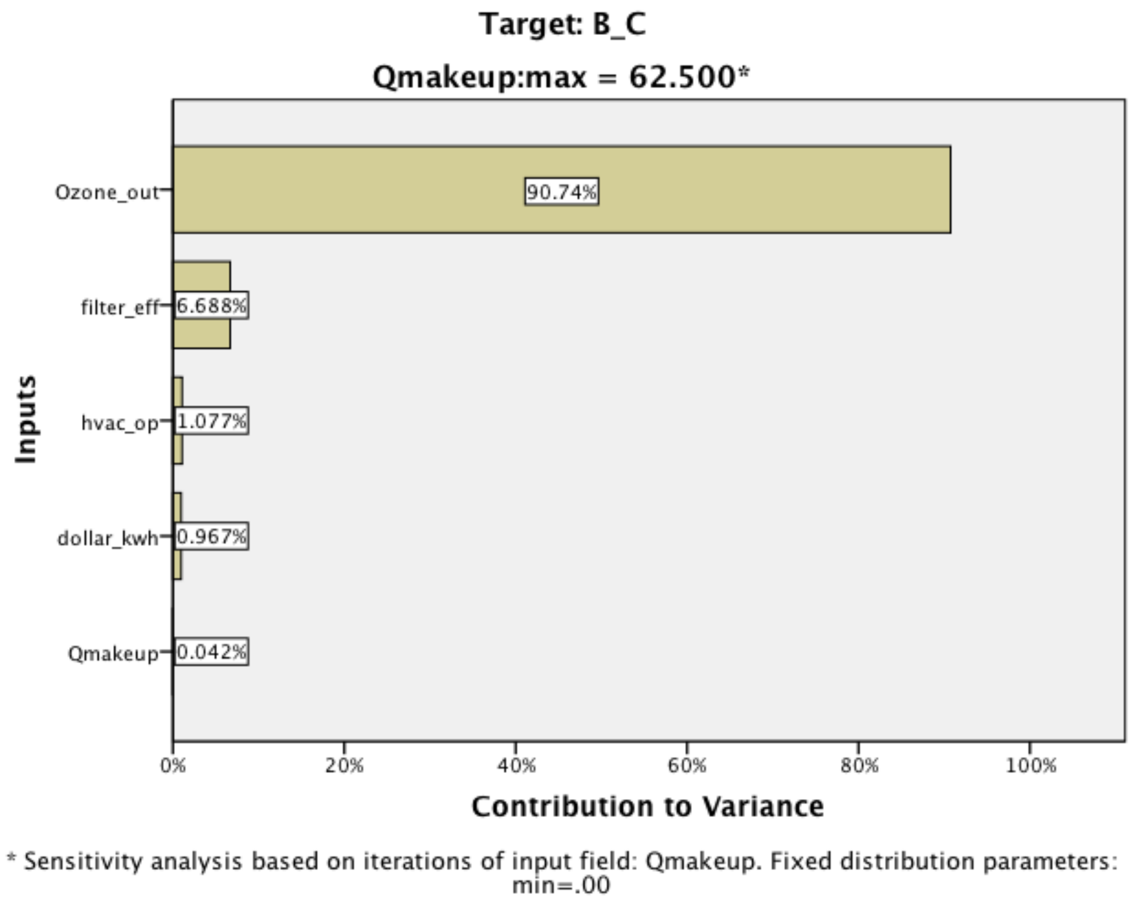
* Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min=.00

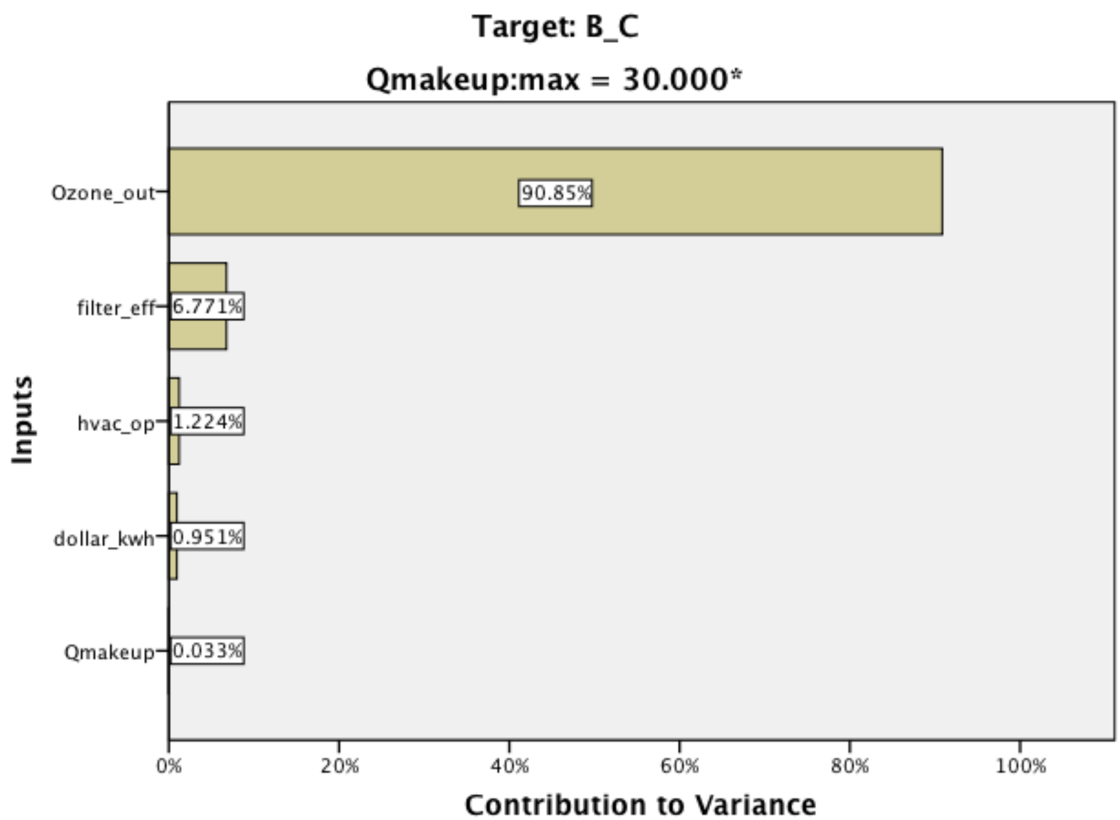
Sensitivity to Input Modulation




Change in B_C for +/- 1 Std. Deviation change in inputs
Qmakeup:max = 30.000*
+1 Std. Deviation
-1 Std. Deviation
Inputs
Ozone_out
filter_eff
hvac_op
dollar_kwh
Qmakeup
-38.07
38.07
-11.59
11.59
4.39
-1.09
-.18
-40.00
-20.00
.00
20.00
40.00
B_C
* Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min=.00

Contribution to Variance





* Sensitivity analysis based on iterations of input field: Qmakeup. Fixed distribution parameters: min=.00

Commercial Office Building Simulation Run

Notes

Output Created		23-APR-2015 08:03:45
Comments		
Input	Data	/Users/joshaldred/Documents/test_22_april_2015.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	68

Simulation Summary

Maximum cases			100000
Total simulated cases			100000
Input filtering	Input: Ozone_out	Minimum value	>= .00
		Maximum value	<= 100.00
Cases filtered			2.3%

Simulation Plan File: /Users/joshaldred/Documents/medofficebldgv1.splan
Cases may be filtered because of either targets or inputs that are outside of the specified ranges. Filtered cases are not included in the simulated cases count.

	Mean	Std. Deviation	Median	Minimum	Maximum	95% Confidence Interval for Mean	
						Lower	Upper
B_C	19.948	43.858	19.174	-113.48	234.46	19.677	20.220

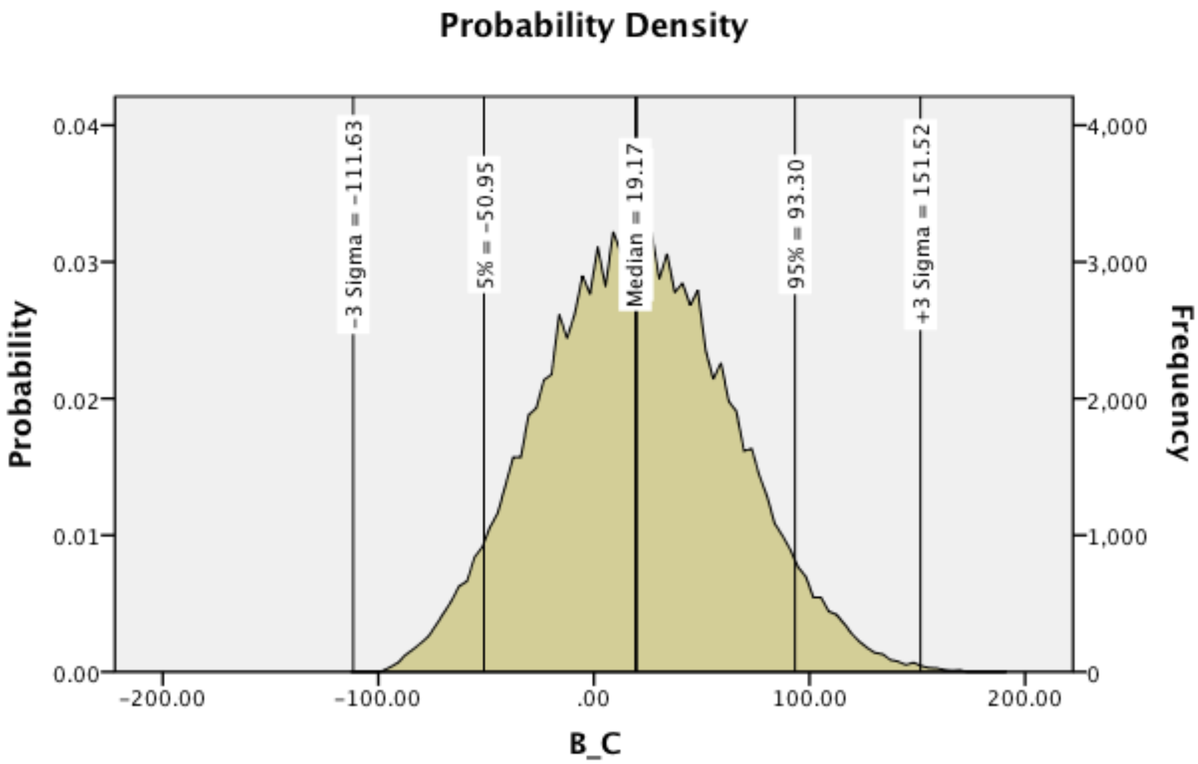
Descriptive Statistics of Scale Inputs

	Mean	Std. Deviation	Minimum	Maximum
Ozone_out	30.777	14.135	.00	96.38
Qmakeup	8502.298	1153.074	6500.01	10499.99
dollar_kwh	.150	.029	.10	.20
filter_eff	.550	.202	.20	.90
hvac_op	.900	.058	.80	1.00

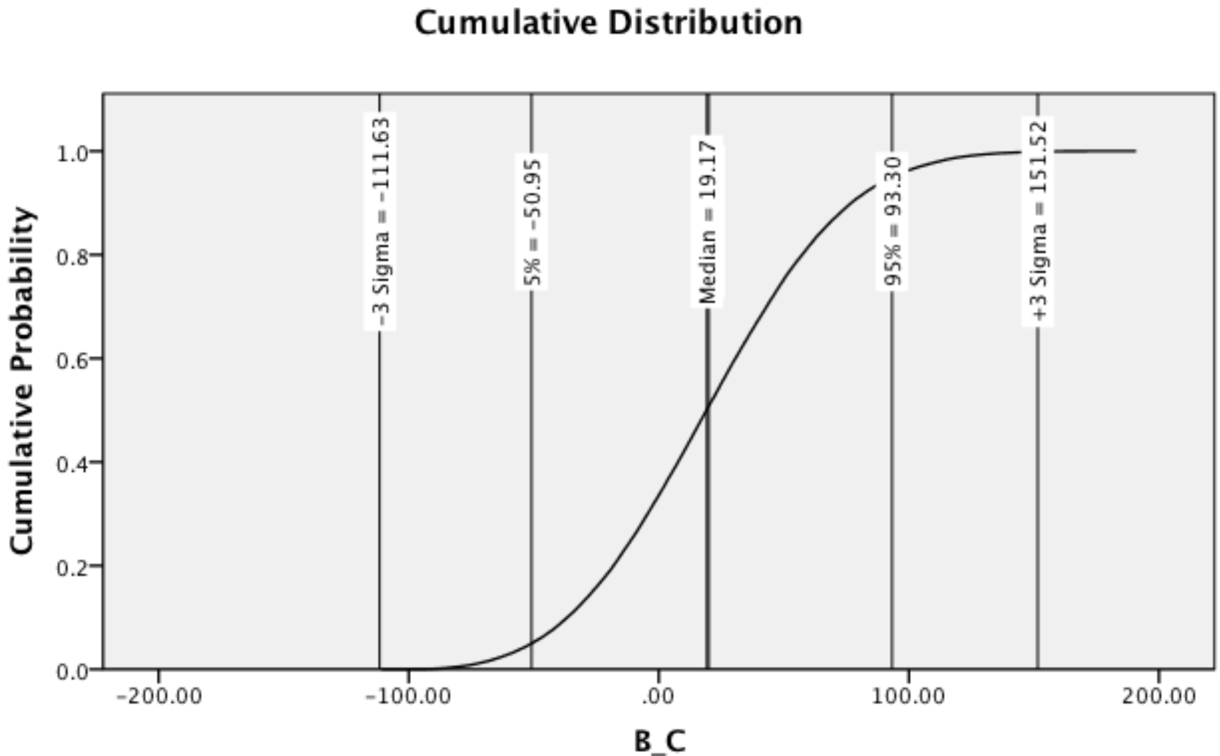
Correlations

	dollar_kwh	filter_eff	hvac_op	Ozone_out	Qmakeup
dollar_kwh	1.000	-.091	-.297	.319	-.116
filter_eff	-.091	1.000	.229	-.060	-.129
hvac_op	-.297	.229	1.000	-.046	.359
Ozone_out	.319	-.060	-.046	1.000	.032
Qmakeup	-.116	-.129	.359	.032	1.000

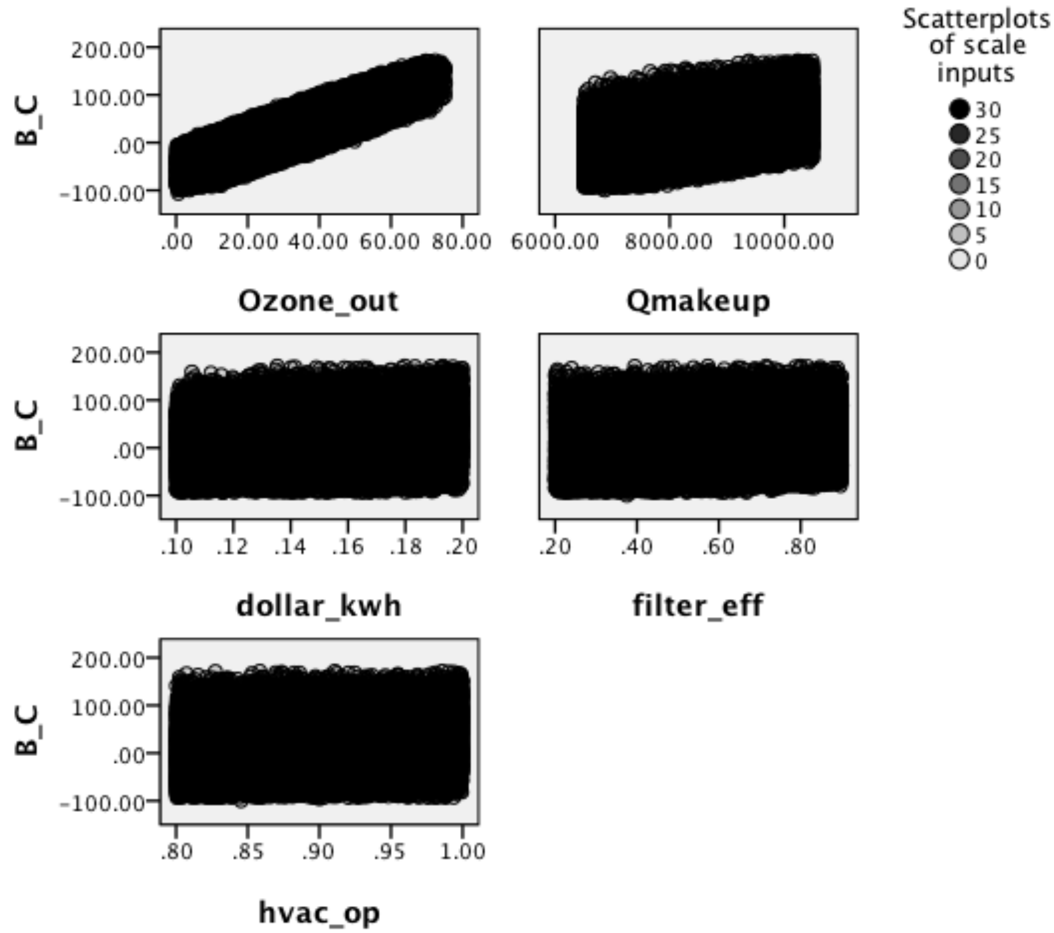
Correlations between simulated inputs may differ from correlations specified for those inputs in the simulation plan.
Excluded fields (fixed inputs and inputs with categorical distributions): A15_24 A1_4 A25_34 A35_44 A45_54 A55_64 A5_14 A65_74 A75_84 A85_plus



< -50.95	-50.95 - 93.30	> 93.30
5%	90%	5%

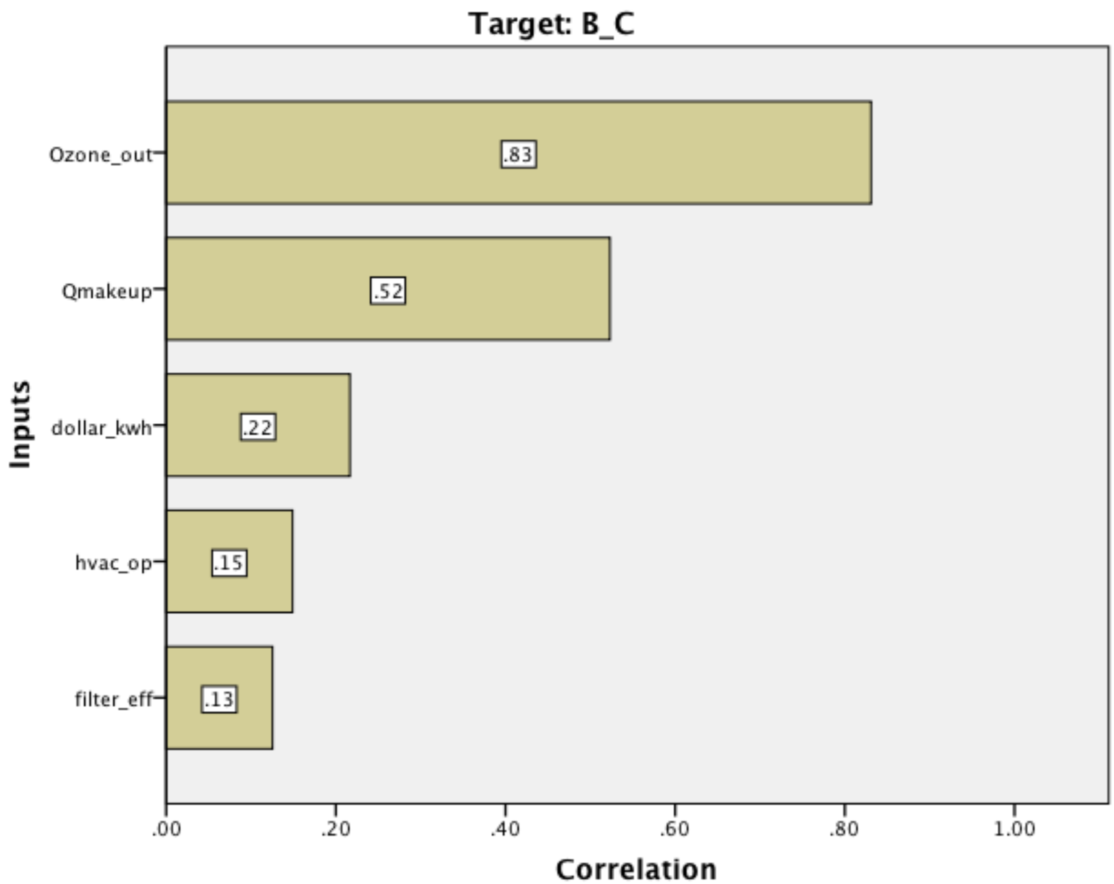


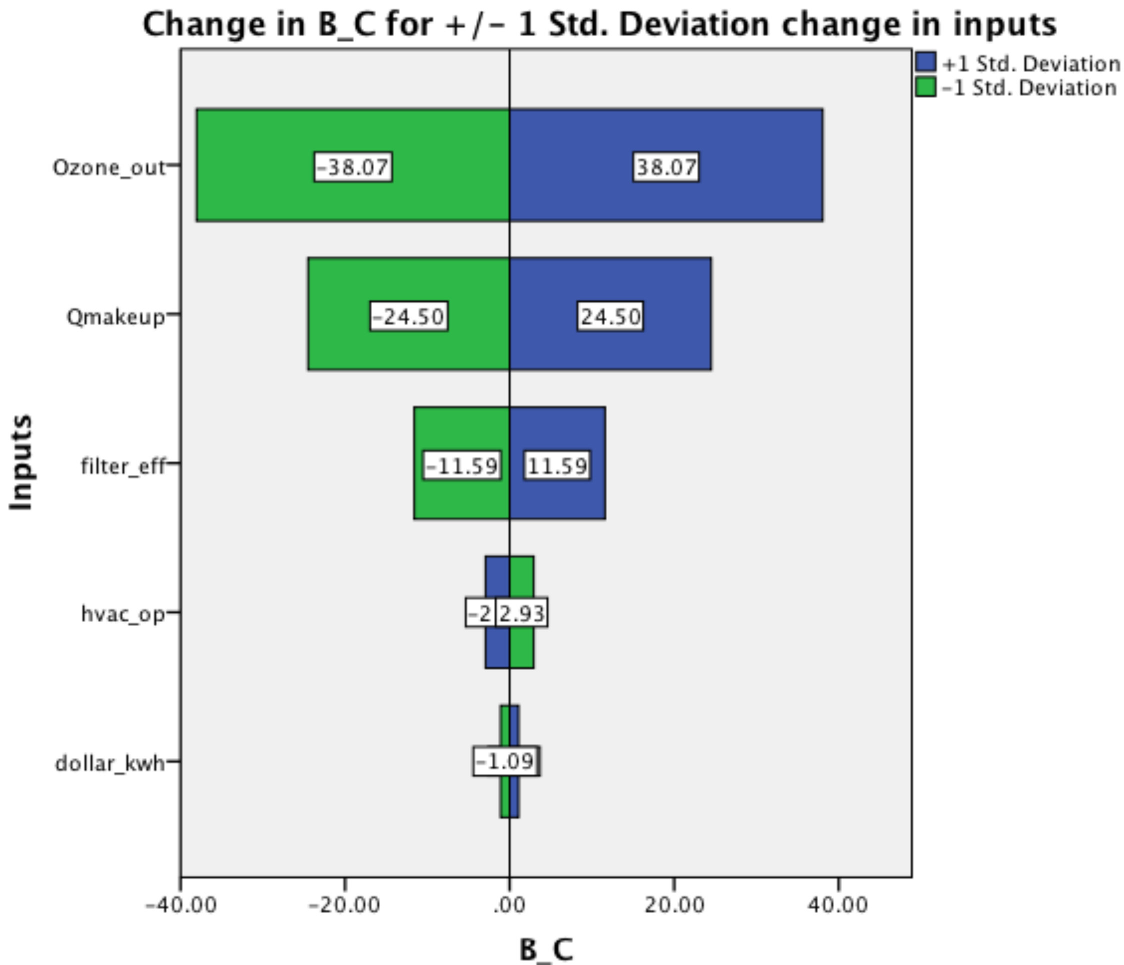
< -50.95	-50.95 - 93.30	> 93.30
5%	90%	5%



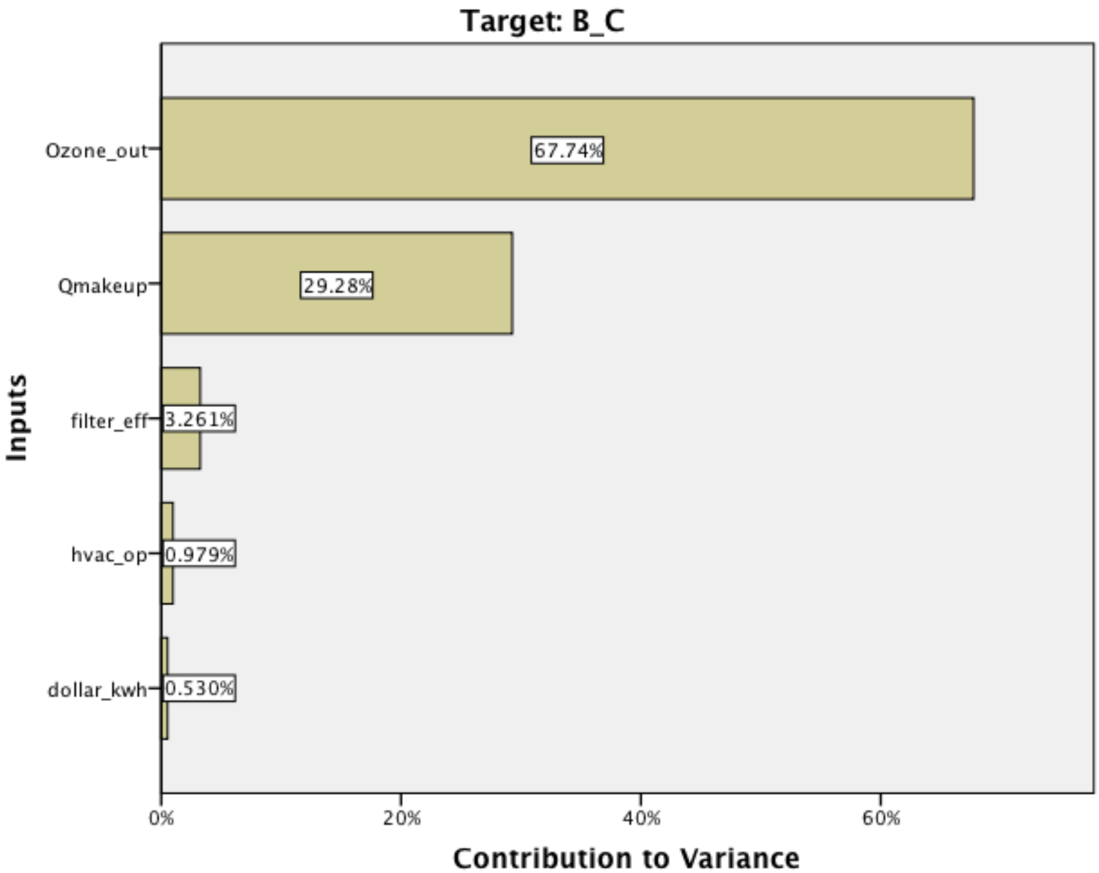
Scatterplots of scale inputs
30
25
20
15
10
5
0
B_C
200.00
100.00
.00
-100.00
.00
20.00
40.00
60.00
80.00
Ozone_out
6000.00
8000.00
10000.00
Qmakeup
.10
.12
.14
.16
.18
.20
dollar_kwh
.20
.40
.60
.80
filter_eff
.80
.85
.90
.95
1.00
hvac_op

Tornado Charts





Change in B_C for +/- 1 Std. Deviation change in inputs
+1 Std. Deviation
-1 Std. Deviation
Inputs
Ozone_out
Qmakeup
filter_eff
hvac_op
dollar_kwh
-38.07
38.07
-24.50
24.50
-11.59
11.59
-2
2.93
-1.09
-40.00
-20.00
.00
20.00
40.00
B_C



Long-Term Healthcare Facility Simulation Run

Notes

Output Created		22-APR-2015 19:56:18
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Files Saved	Simulated Cases File	/Users/joshaldred/Documents/SPSS/NursingHomev1.splan

Simulation Summary

Maximum cases			100000
Total simulated cases			100000
Input filtering	Input: Ozone_out	Minimum value	>= .00
		Maximum value	<= 100.00
Cases filtered			2.3%

Simulation Plan File:
/Users/joshaldred/Documents/SPSS/NursingHomev1.splan
Cases may be filtered because of either targets or inputs that are outside of the specified ranges. Filtered cases are not included in the simulated cases count.

						95% Confidence Interval for Mean	
	Mean	Std. Deviation	Median	Minimum	Maximum	Lower	Upper
B_C	448.150	47.969	447.309	303.33	656.94	447.852	448.447

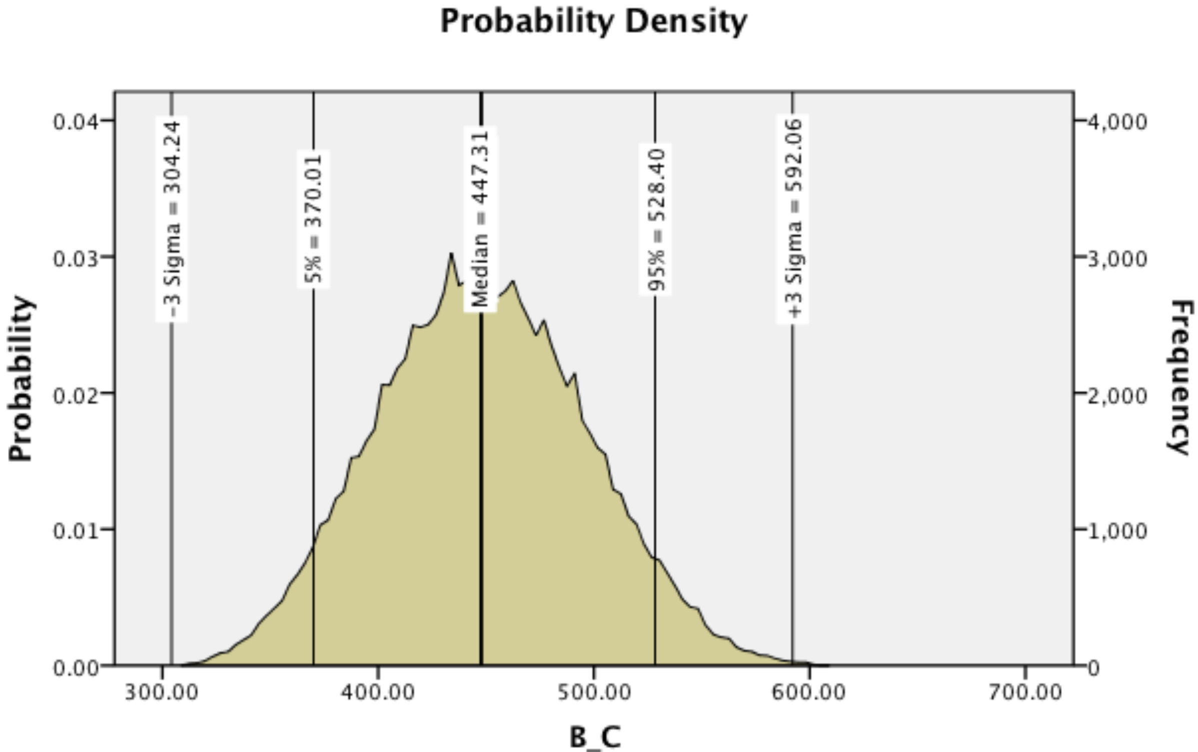
Descriptive Statistics of Scale Inputs

	Mean	Std. Deviation	Minimum	Maximum
A85_plus	.150	.023	.11	.19
Ozone_out	30.778	14.106	.00	97.93
dollar_kwh	.150	.029	.10	.20
filter_eff	.550	.202	.20	.90
hvac_op	.900	.058	.80	1.00

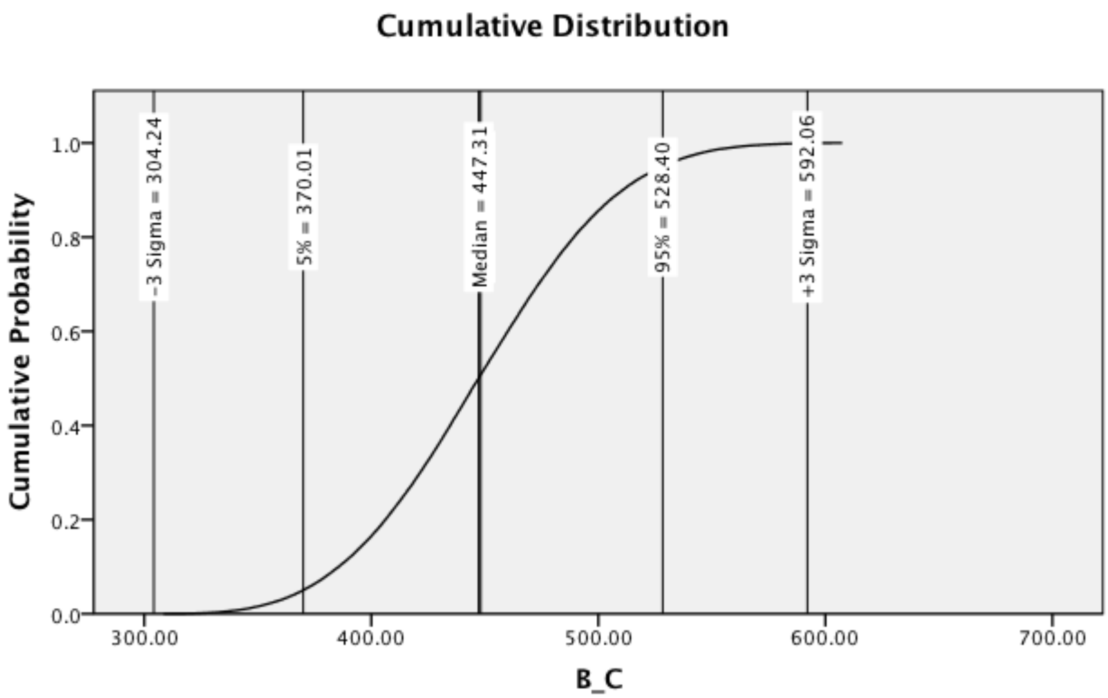
Correlations

	A85_plus	dollar_kwh	filter_eff	hvac_op	Ozone_out
A85_plus	1.000	-.409	-.254	.130	.008
dollar_kwh	-.409	1.000	-.120	.354	-.002
filter_eff	-.254	-.120	1.000	.247	-.057
hvac_op	.130	.354	.247	1.000	.007
Ozone_out	.008	-.002	-.057	.007	1.000

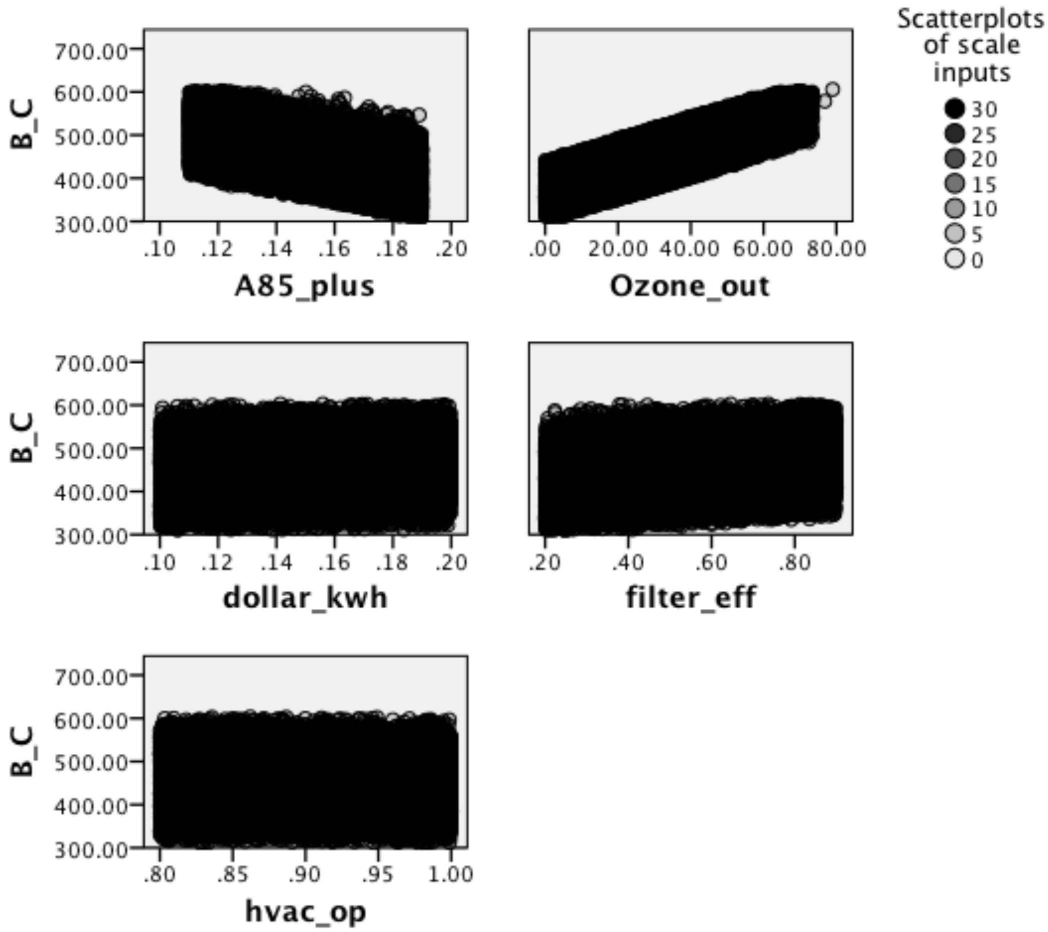
Correlations between simulated inputs may differ from correlations specified for those inputs in the simulation plan.
Excluded fields (fixed inputs and inputs with categorical distributions): A15_24 A1_4 A25_34 A35_44 A45_54 A55_64 A5_14 A65_74 A75_84 Qmakeup



< 370.01	370.01 - 528.40	> 528.40
5%	90%	5%

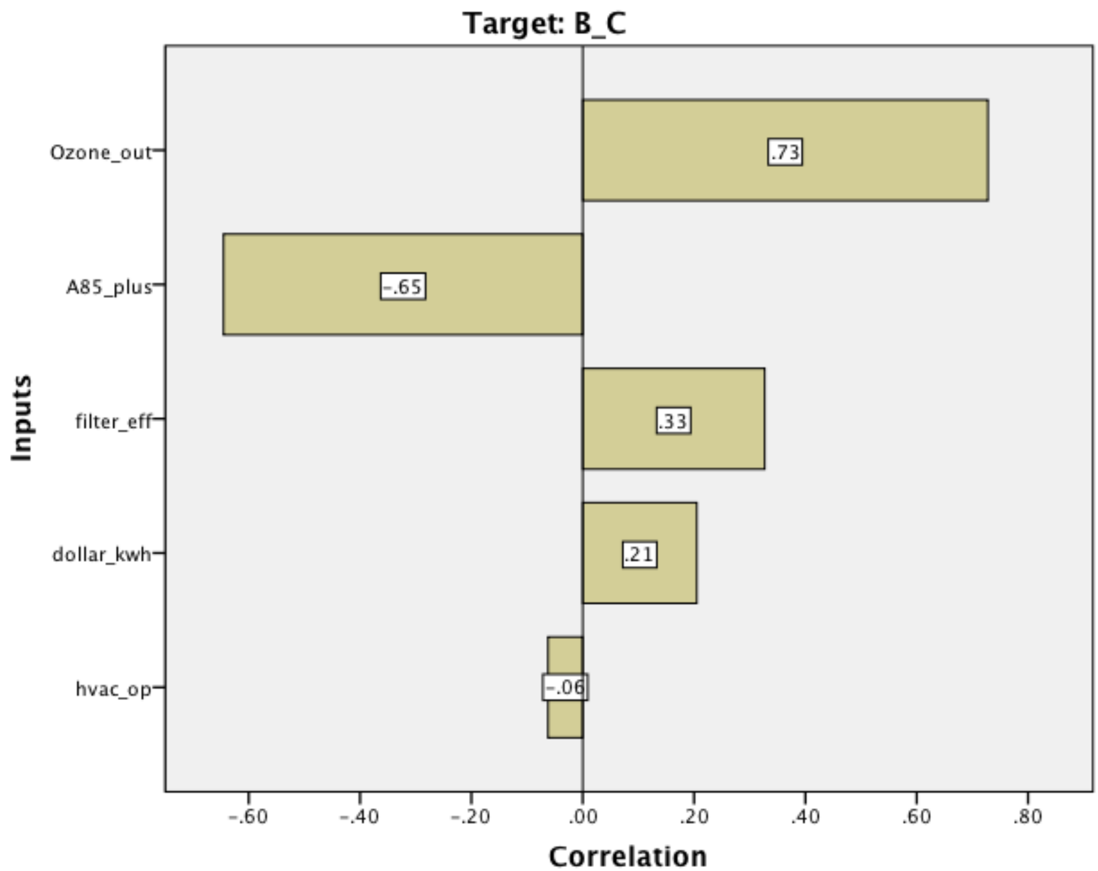


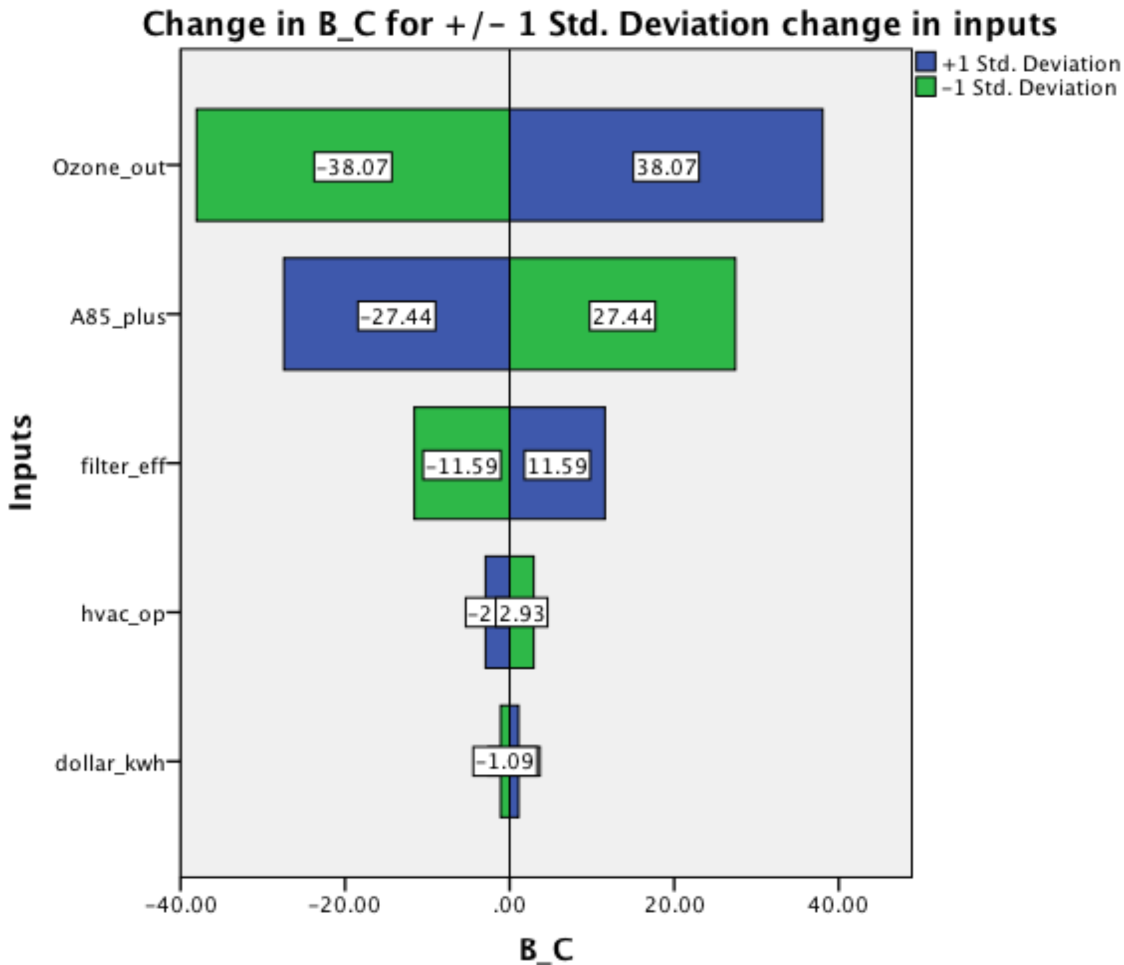
< 370.01	370.01 – 528.40	> 528.40
5%	90%	5%

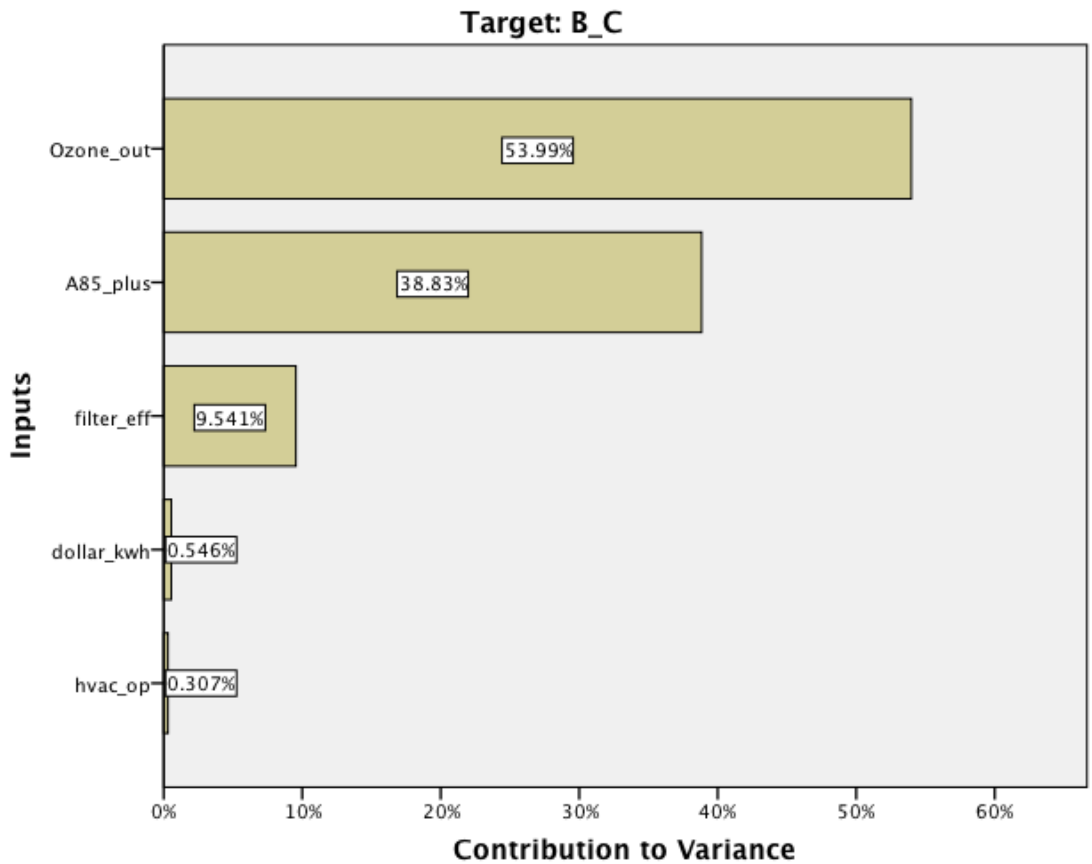


B_C
700.00
600.00
500.00
400.00
300.00
.10 .12 .14 .16 .18 .20
A85_plus
.00 20.00 40.00 60.00 80.00
Ozone_out
Scatterplots of scale inputs
30
25
20
15
10
5
0
dollar_kwh
.20 .40 .60 .80
filter_eff
.80 .85 .90 .95 1.00
hvac_op

Tornado Charts




Change in B_C for +/- 1 Std. Deviation change in inputs
+1 Std. Deviation
-1 Std. Deviation
Inputs
Ozone_out
A85_plus
filter_eff
hvac_op
dollar_kwh
-38.07
38.07
-27.44
27.44
-11.59
11.59
-2
2.93
-1.09
-40.00
-20.00
.00
20.00
40.00
B_C



K-12 Schools Simulation Run

Notes

Output Created		22-APR-2015 20:10:58
Comments		
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	N of Rows in Working Data File	68

Simulation Summary

Maximum cases			100000
Total simulated cases			100000
Input filtering	Input: Ozone_out	Minimum value	>= .00
		Maximum value	<= 100.00
Cases filtered			2.3%

Simulation Plan File:
/Users/joshaldred/Documents/SPSS/K12Schoolv1.splan
Cases may be filtered because of either targets or inputs that are outside of the specified ranges. Filtered cases are not included in the simulated cases count.

	Mean	Std. Deviation	Median	Minimum	Maximum	95% Confidence Interval for Mean	
						Lower	Upper
B_C	3.104	37.116	1.803	-98.67	180.60	2.874	3.334

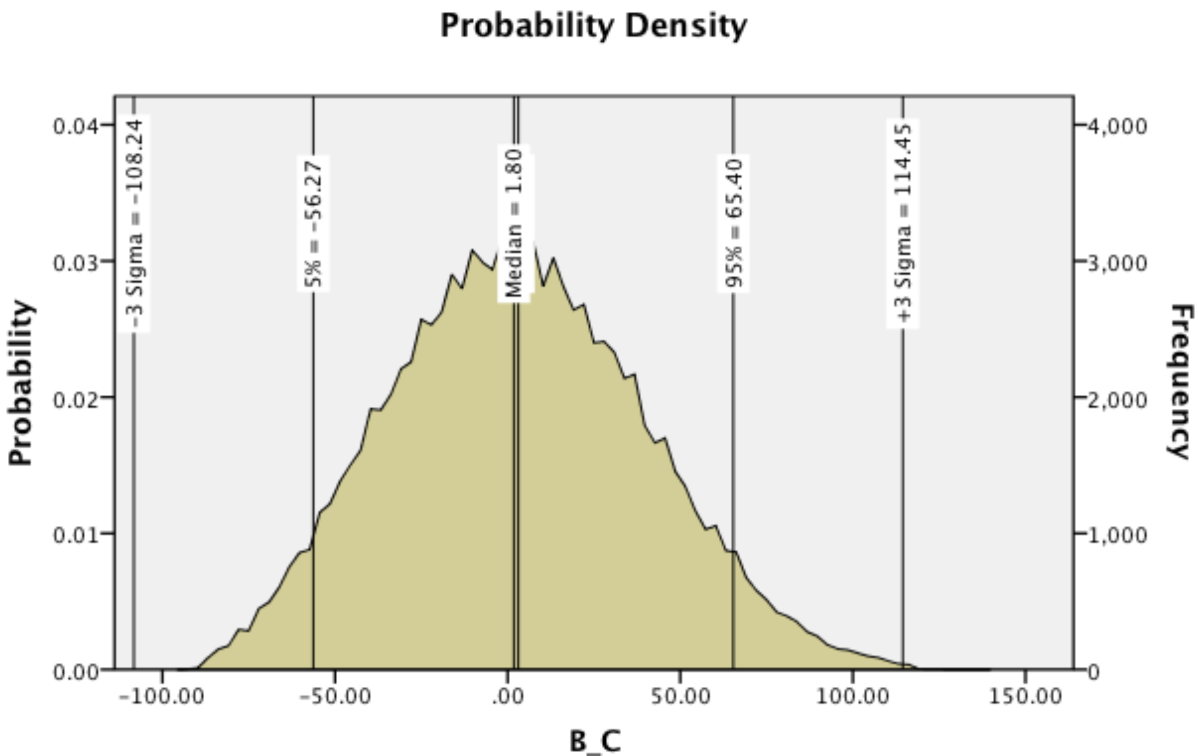
Descriptive Statistics of Scale Inputs

	Mean	Std. Deviation	Minimum	Maximum
Ozone_out	30.835	14.151	.00	95.63
dollar_kwh	.150	.029	.10	.20
filter_eff	.548	.202	.20	.90
hvac_op	.900	.058	.80	1.00

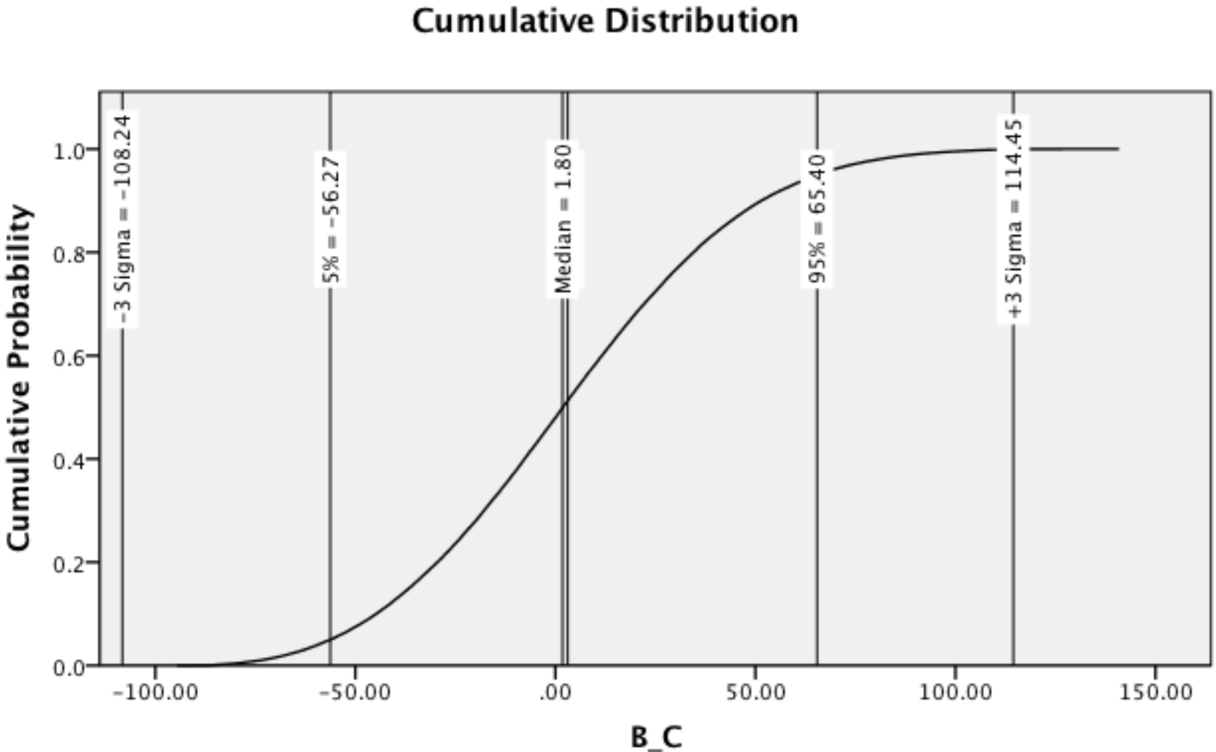
Correlations

	dollar_kwh	filter_eff	hvac_op	Ozone_out
dollar_kwh	1.000	-.024	-.302	.288
filter_eff	-.024	1.000	.240	-.088
hvac_op	-.302	.240	1.000	-.044
Ozone_out	.288	-.088	-.044	1.000

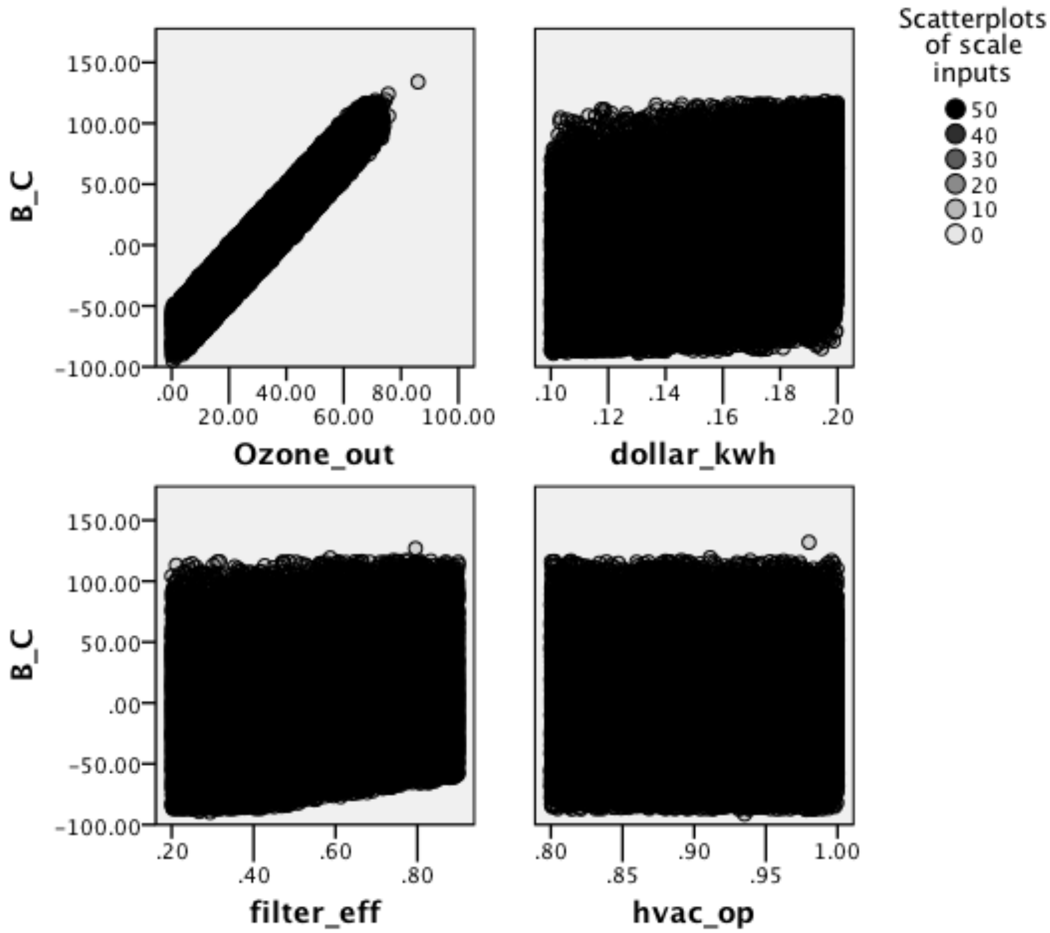
Correlations between simulated inputs may differ from correlations specified for those inputs in the simulation plan.
Excluded fields (fixed inputs and inputs with categorical distributions): A15_24 A1_4 A25_34 A35_44 A45_54 A55_64 A5_14 A65_74 A75_84 A85_plus Qmakeup



< -56.27	-56.27 - 65.40	> 65.40
5%	90%	5%

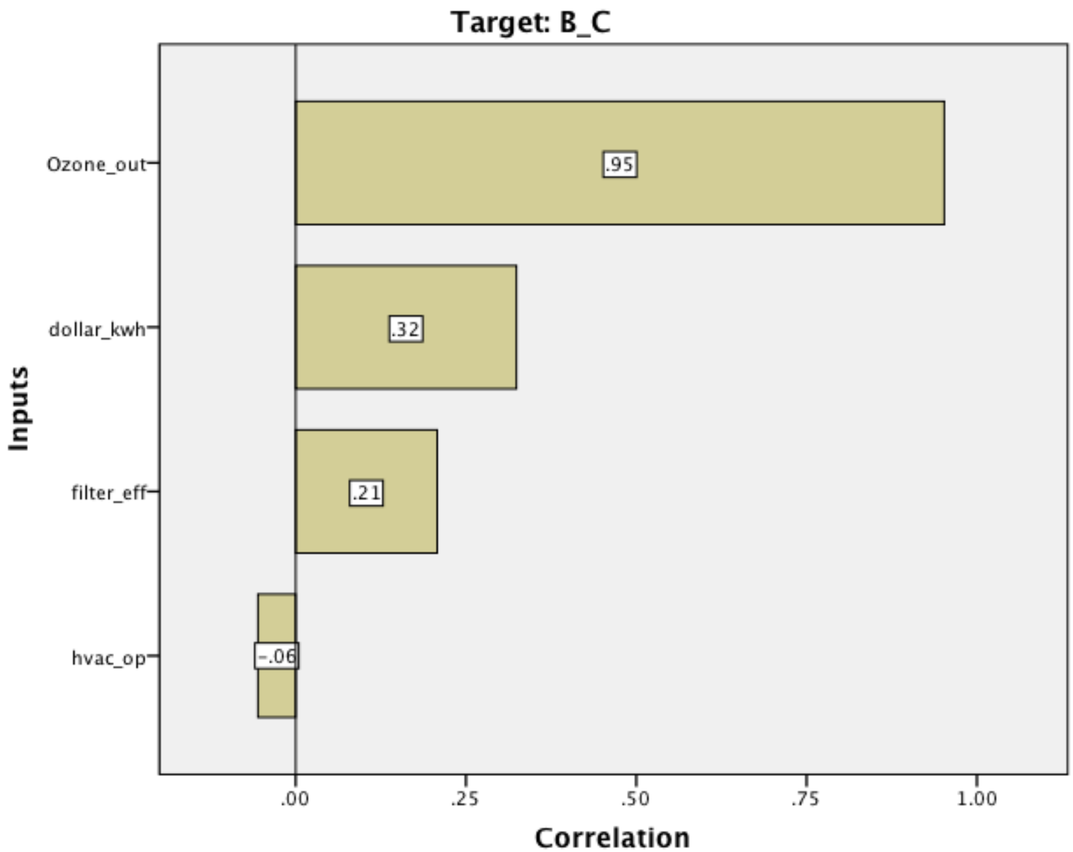


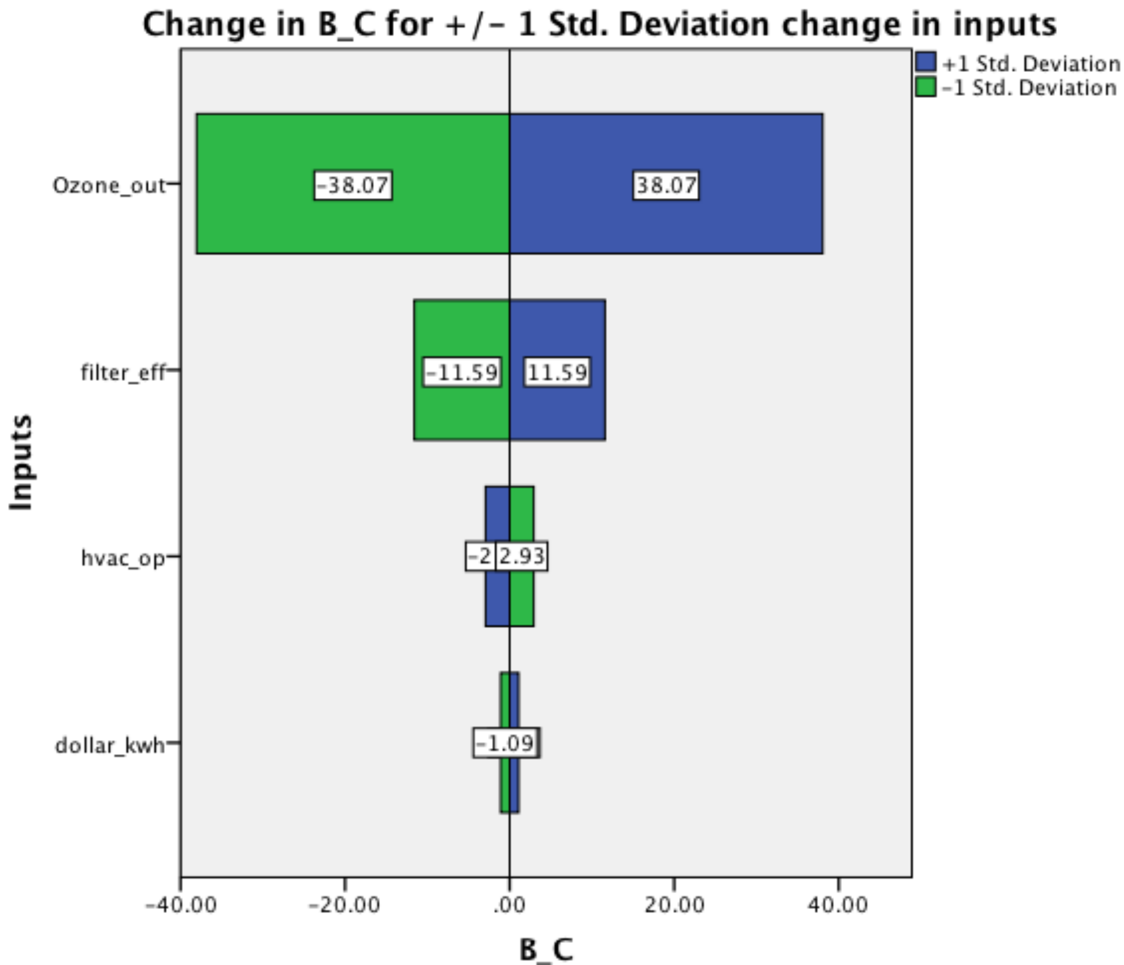
< -56.27	-56.27 - 65.40	> 65.40
5%	90%	5%

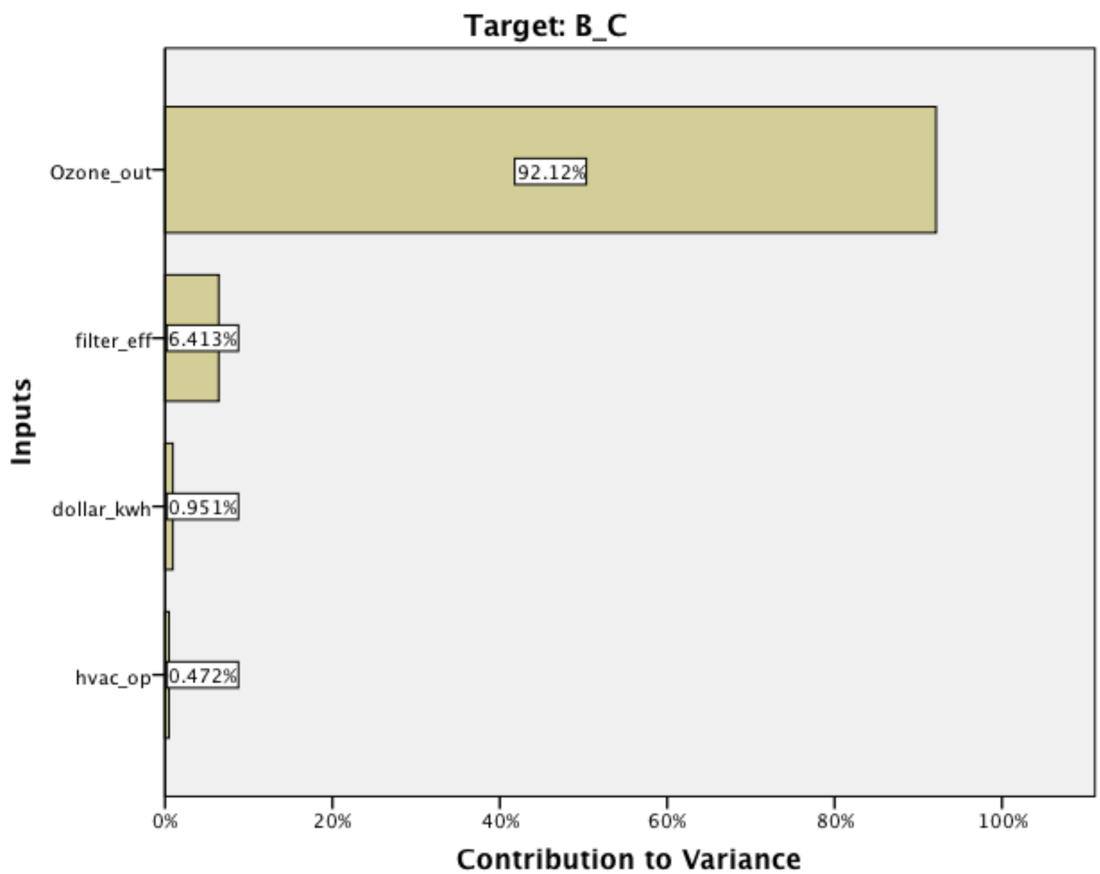


Scatterplots of scale inputs
50
40
30
20
10
0
B_C
150.00
100.00
50.00
.00
-50.00
-100.00
.00
20.00
40.00
60.00
80.00
100.00
Ozone_out
.10
.12
.14
.16
.18
.20
dollar_kwh
.20
.40
.60
.80
filter_eff
.80
.85
.90
.95
1.00
hvac_op

Tornado Charts




Change in B_C for +/- 1 Std. Deviation change in inputs
+1 Std. Deviation
-1 Std. Deviation
Inputs
Ozone_out
filter_eff
hvac_op
dollar_kwh
-38.07
38.07
-11.59
11.59
-2
2.93
-1.09
-40.00
-20.00
.00
20.00
40.00
B_C



Target: B_C
Ozone_out
92.12%
filter_eff
6.413%
dollar_kwh
0.951%
hvac_op
0.472%
Inputs
0%
20%
40%
60%
80%
100%
Contribution to Variance

References

Adams, W. C. (2006). Comparison of chamber 6.6-h exposures to 0.04-0.08 PPM ozone via square-wave and triangular profiles on pulmonary responses. *Inhalation Toxicology*, *18*(2), 127–136. http://doi.org/10.1080/08958370500306107

Aldred, J., Darling, E., Morrison, G., & Siegel, J., Corsi, R. (2005). Benefit-Cost Analysis of Commercially Available Activated Carbon Filters for Indoor Ozone Removal in Residential Buildings.

Alvarez, P. M., Masa, F. J., Jaramillo, J., Beltran, F. J., & Gomez-Serrano, V. (2008). Kinetics of ozone decomposition by granular activated carbon. *Industrial & Engineering Chemistry Research*, *47*(8), 2545–2553. http://doi.org/10.1021/ie071360z

Anderson, G. B., Krall, J. R., Peng, R. D., & Bell, M. L. (2012). Is the Relation Between Ozone and Mortality Confounded by Chemical Components of Particulate Matter? Analysis of 7 Components in 57 US Communities. *American Journal of Epidemiology*, *176*(8), 726–732. http://doi.org/10.1093/aje/kws188

Anderson, H. R., Spix, C., Medina, S., Schouten, J. P., Castellsague, J., Rossi, G., … Katsouyanni, K. (1997). Air pollution and daily admissions for chronic obstructive pulmonary disease in 6 European cities: Results from the APHEA project. *European Respiratory Journal*, *10*(5), 1064–1071. http://doi.org/10.1183/09031936.97.10051064

Anderson, S. E., Franko, J., Jackson, L. G., Wells, J. R., Ham, J. E., & Meade, B. J. (2012). Irritancy and Allergic Responses Induced by Exposure to the Indoor Air Chemical 4-Oxopentanal. *Toxicological Sciences*, *127*(2), 371–381. http://doi.org/10.1093/toxsci/kfs102

Anderson, S. E., Jackson, L. G., Franko, J., & Wells, J. R. (2010). Evaluation of Dicarbonyls Generated in a Simulated Indoor Air Environment Using an In Vitro Exposure System. *Toxicological Sciences*, *115*(2), 453–461. http://doi.org/10.1093/toxsci/kfq067

Anderson, S. E., Wells, J. R., Fedorowicz, A., Butterworth, L. F., Meade, B. J., & Munson, A. E. (2007). Evaluation of the contact and respiratory sensitization potential of volatile organic compounds generated by simulated indoor air chemistry. *Toxicological Sciences*, *97*(2), 355–363. http://doi.org/10.1093/toxsci/kfm043

Apte, M. G., Buchanan, I. S. H., & Mendell, M. J. (2008). Outdoor ozone and building-related symptoms in the BASE study. *Indoor Air*, *18*(2), 156–170. http://doi.org/10.1111/j.1600-0668.2008.00521.x

ASHRAE-American Society of Heating, Ventilation, and Air-Conditioning Engineers. (2008). *Ventilation of Health Care Facilities*. Atlanta, GA.

ASHRAE-American Society of Heating, Ventilation, and Air-Conditioning Engineers. (2013a). *Energy Standard for Buildings Except Low-Rise Residential Buildings* (No. ASHRAE Standard 90.1-2013). Atlanta, GA.

ASHRAE-American Society of Heating, Ventilation, and Air-Conditioning Engineers. (2013b). *Ventilation and Acceptable Indoor Air Quality in Low-Rise Residential Buildings* (No. No. ASHRAE Standard 62.2-2013). Atlanta, GA.

ASHRAE-American Society of Heating, Ventilation, and Air-Conditioning Engineers. (2013c). *Ventilation for Acceptable Indoor Air Quality* (No. ASHRAE Standard 62.1-2013). Atlanta, GA.

ASHRAE - American Society of Heating, Refrigeration, and Air-Conditioning Engineers. (2009). *ASHRAE Handbook - Fundamentals*.

Atkinson, R., & Arey, J. (2003). Gas-phase tropospheric chemistry of biogenic volatile organic compounds: a review. *Atmospheric Environment*, *37*, S197–S219. http://doi.org/10.1016/S1352-2310(03)00391-1

Azimi, P., & Stephens, B. (2013). HVAC filtration for controlling infectious airborne disease transmission in indoor environments: Predicting risk reductions and operational costs. *Building and Environment*, *70*, 150–160.

Beko, G., Clausen, G., & Weschler, C. J. (2008). Sensory pollution from bag filters, carbon filters and combinations. *Indoor Air*, *18*(1), 27–36. http://doi.org/10.1111/j.1600-0668.2007.00501.x

Beko, G., Fadeyi, M. O., Clausen, G., & Weschler, C. J. (2009). Sensory pollution from bag-type fiberglass ventilation filters: Conventional filter compared with filters containing various amounts of activated carbon. *Building and Environment*, *44*(10), 2114–2120. http://doi.org/10.1016/j.buildenv.2009.03.002

Bell, M. L., & Dominici, F. (2008). Effect modification by community characteristics on the short-term effects of ozone exposure and mortality in 98 US communities. *American Journal of Epidemiology*, *167*(8), 986–997. http://doi.org/10.1093/aje/kwm396

Bell, M. L., Dominici, F., & Samet, J. M. (2005). A meta-analysis of time-series studies of ozone and mortality with comparison to the national morbidity, mortality, and air pollution study. *Epidemiology*, *16*(4), 436–445. http://doi.org/10.1097/01.ede.0000165817.40152.85

Bell, M. L., Ebisu, K., Peng, R. D., & Dominici, F. (2009). Adverse Health Effects of Particulate Air Pollution Modification by Air Conditioning. *Epidemiology*, *20*(5), 682–686. http://doi.org/10.1097/EDE.0b013e3181aba749

Bell, M. L., McDermott, A., Zeger, S. L., Samet, J. M., & Dominici, F. (2004). Ozone and short-term mortality in 95 US urban communities, 1987-2000. *Jama-Journal of the American Medical Association*, *292*(19), 2372–2378. http://doi.org/10.1001/jama.292.19.2372

Bell, M. L., Peng, R. D., & Dominici, F. (2006). The exposure-response curve for ozone and risk of mortality and the adequacy of current ozone regulations. *Environmental Health Perspectives*, *114*(4), 532–536. http://doi.org/10.1289/ehp.8816

Berman, J. D., Fann, N., Hollingsworth, J. W., Pinkerton, K. E., Rom, W. N., Szema, A. M., Curriero, F. C. (2012). Health Benefits from Large-Scale Ozone Reduction in the United States. *Environmental Health Perspectives*, *120*(10), 1404–1410.

Blumenthal, K. J., Saulsgiver, K. A., Norton, L., Troxel, A. B., Anarella, J. P., Gesten, F. C., Volpp, K. G. (2013). Medicaid Incentive Programs To Encourage Healthy Behavior Show Mixed Results To Date And Should Be Studied And Improved. *Health Affairs*, *32*(3), 497–507. http://doi.org/10.1377/hlthaff.2012.0431

Bobinac, A., van Exel, J., Rutten, F. F. H., & Brouwer, W. B. F. (2014). The Value of a QALY: Individual Willingness to Pay for Health Gains Under Risk. *Pharmacoeconomics*, *32*(1), 75–86. http://doi.org/10.1007/s40273-013-0110-1

Brown, J. S., Bateson, T. F., & McDonnell, W. F. (2008). Effects of exposure to 0.06 ppm ozone on FEV1 in humans: A secondary analysis of existing data. *Environmental Health Perspectives*, *116*(8), 1023–1026. http://doi.org/10.1289/ehp.11396

Buchanan, I. S. H., Mendell, M. J., Mirer, A. G., & Apte, M. G. (2008). Air filter materials, outdoor ozone and building-related symptoms in the BASE study. *Indoor Air*, *18*(2), 144–155. http://doi.org/10.1111/j.1600-0668.2008.00519.x

Burmaster, D. E., & Hull, D. A. (1997). Using Lognormal distributions and Lognormal probability plots in probabilistic risk assessments. *Human and Ecological Risk Assessment*, *3*(2), 235–255.

Burnett, R. T., Smith-Doiron, M., Stieb, D., Cakmak, S., & Brook, J. R. (1999). Effects of particulate and gaseous air pollution on cardiorespiratory hospitalizations. *Archives of Environmental Health*, *54*(2), 130–139.

Cetin, K**.,** Novoselac, A. (2015). Single and multi-family residential HVAC system operational characteristics and use patterns in a cooling-dominated climate. Manuscript submitted for preparation.

Checkoway, H., Boffetta, P., Mundt, D. J., & Mundt, K. A. (2012). Critical review and synthesis of the epidemiologic evidence on formaldehyde exposure and risk of leukemia and other lymphohematopoietic malignancies. *Cancer Causes & Control*, *23*(11), 1747–1766. http://doi.org/10.1007/s10552-012-0055-2

Chen, C., Zhao, B., & Weschler, C. J. (2012a). Assessing the Influence of Indoor Exposure to “Outdoor Ozone” on the Relationship between Ozone and Short-term Mortality in US

Communities. *Environmental Health Perspectives*, *120*(2), 235–240. http://doi.org/10.1289/ehp.1103970

Chen, C., Zhao, B., & Weschler, C. J. (2012b). Indoor Exposure to "Outdoor PM10" Assessing Its Influence on the Relationship Between PM10 and Short-term Mortality in US Cities. *Epidemiology*, *23*(6), 870–878. http://doi.org/10.1097/EDE.0b013e31826b800e

Chen, L., Jennison, B. L., Yang, W., & Omaye, S. T. (2000). Elementary school absenteeism and air pollution. *Inhalation Toxicology*, *12*(11), 997–1016.

Chen, X., & Hopke, P. K. (2009). A chamber study of secondary organic aerosol formation by linalool ozonolysis. *Atmospheric Environment*, *43*(25), 3935–3940. http://doi.org/10.1016/j.atmosenv.2009.04.033

Chen, X., & Hopke, P. K. (2010). A chamber study of secondary organic aerosol formation by limonene ozonolysis. *Indoor Air*, *20*(4), 320–328. http://doi.org/10.1111/j.1600-0668.2010.00656.x

Coleman, B. K., Destaillats, H., Hodgson, A. T., & Nazaroff, W. W. (2008). Ozone consumption and volatile byproduct formation from surface reactions with aircraft cabin materials and clothing fabrics. *Atmospheric Environment*, *42*(4), 642–654. http://doi.org/10.1016/j.atmosenv.2007.10.001

Collinge, W., Landis, A. E., Jones, A. K., Schaefer, L. A., & Bilec, M. M. (2013). Indoor environmental quality in a dynamic life cycle assessment framework for whole buildings: Focus on human health chemical impacts. *Building and Environment*, *62*, 182–190. http://doi.org/10.1016/j.buildenv.2013.01.015

Cometto-Muniz, J. E., & Abraham, M. H. (2010). Odor Detection by Humans of Lineal Aliphatic Aldehydes and Helional as Gauged by Dose-Response Functions. *Chemical Senses*, *35*(4), 289–299. http://doi.org/10.1093/chemse/bjq018

Corsi, R., Aldred, J., Darling, E., Morrison, G., & Siegel, J. (2014). *Literature and Product Review and Cost Benefit Analysis of Commercially Available Ozone Air Cleaning for HVAC Systems* (No. ASHRAE RP 1491). American Society of Heating, Refrigeration, and Air Conidtioning Engineers.

Cros, C. J., Morrison, G. C., Siegel, J. A., & Corsi, R. L. (2012). Long-term performance of passive materials for removal of ozone from indoor air. *Indoor Air*, *22*(1), 43–53. http://doi.org/10.1111/j.1600-0668.2011.00734.x

Delfino, R. J., Staimer, N., Tjoa, T., Gillen, D. L., Schauer, J. J., & Shafer, M. M. (2013). Airway inflammation and oxidative potential of air pollutant particles in a pediatric asthma panel. *Journal of Exposure Science and Environmental Epidemiology*, *23*(5), 466–473. http://doi.org/10.1038/jes.2013.25

Dusenbury, J. S., & Cannon, F. S. (1996). Advanced oxidant reactivity pertaining to granular activated carbon beds for air pollution control. *Carbon*, *34*(12), 1577–1589. http://doi.org/10.1016/S0008-6223(96)00113-3

Fadeyi, M. O. (2014). Mass balance modeling of building recirculation rates and filtration efficiencies effects on secondary organic aerosols derived from ozone-initiated chemistry. *Building Simulation*, *7*(2), 165–173. http://doi.org/10.1007/s12273-013-0139-2

Fadeyi, M. O., Weschler, C. J., & Tham, K. W. (2009). The impact of recirculation, ventilation and filters on secondary organic aerosols generated by indoor chemistry.

Atmospheric Environment, *43*(22-23), 3538–3547. http://doi.org/10.1016/j.atmosenv.2009.04.017

Fadeyi, M. O., Weschler, C. J., Tham, K. W., Wu, W. Y., & Sultan, Z. M. (2013). Impact of Human Presence on Secondary Organic Aerosols Derived from Ozone-Initiated Chemistry in a Simulated Office Environment. *Environmental Science & Technology*, *47*(8), 3933–3941. http://doi.org/10.1021/es3050828

Fan, Z. H., Lioy, P., Weschler, C., Fiedler, N., Kipen, H., & Zhang, J. F. (2003). Ozone-initiated reactions with mixtures of volatile organic compounds under simulated indoor conditions. *Environmental Science & Technology*, *37*(9), 1811–1821. http://doi.org/10.1021/es026231i

Fann, N. (2014, January). Correspondence with J. Aldred. Austin, TX.

Fisk, W. (2009). Ozone Removal by Filters Containing Activated Carbon: A Pilot Study. In *Proceedings of the 9th International Conference on Healthy Buildings*. Syracuse, NY.

Fisk, W. J., Black, D., & Brunner, G. (2011). Benefits and costs of improved IEQ in US offices. *Indoor Air*, *21*(5), 357–367. http://doi.org/10.1111/j.1600-0668.2011.00719.x

Fisk, W. J., & Rosenfeld, A. H. (1997). Estimates of improved productivity and health from better indoor environments. *Indoor Air-International Journal of Indoor Air Quality and Climate*, *7*(3), 158–172. http://doi.org/10.1111/j.1600-0668.1997.t01-1-00002.x

Gall, E., Siegel, J. A., & Corsi, R. (2011). Zero-Energy Removal of Ozone in Residences. *Ashrae: Transactions 2011, Vol 117, Pt 1*, *117*, 411–418.

Ginestet, A., Pugnet, D., Tissot, A., & Henninot, M. (2013). On-Site Particle and Gas Filtration Efficiencies of Air Handling Unit Filters in Industrial and Non Industrial Building. *International Journal of Ventilation*, *12*(2), 151–158.

Glad, J. A., Brink, L. L., Talbott, E. O., Lee, P. C., Xu, X., Saul, M., & Rager, J. (2012). The Relationship of Ambient Ozone and PM2.5 Levels and Asthma Emergency Department Visits: Possible Influence of Gender and Ethnicity. *Archives of Environmental & Occupational Health*, *67*(2), 103–108. http://doi.org/10.1080/19338244.2011.598888

Godwin, C., & Batterman, S. (2007). Indoor air quality in Michigan schools. *Indoor Air*, *17*(2), 109–121. http://doi.org/10.1111/j.1600-0668.2006.00459.x

Gordon, S. M., Callahan, P. J., Nishioka, M. G., Brinkman, M. C., O'Rourke, M. K., Lebowitz, M. D., & Moschandreas, M. J. (1999). Residential environmental measurements in the National Human Exposure Assessment Survey (NHEXAS) pilot study in Arizona: preliminary results for pesticides and VOCs. *Journal of Exposure Analysis and Environmental Epidemiology*, *9*(5), 456–470. http://doi.org/10.1038/sj.jea.7500042

Grosjean, D., Williams, E., Grosjean, E., Andino, J., & Seinfeld, J. (1993). Atmospheric Oxidation of Biogenic Hydrocarbons -- Reaction of Ozone with Beta-Pinene, D-Limonene and Trans-Caryophyllene. *Environmental Science & Technology*, *27*(13), 2754–2758. http://doi.org/10.1021/es00049a014

Grosjean, E., & Grosjean, D. (1996). Carbonyl products of the gas-phase reaction of ozone with 1-alkenes. *Atmospheric Environment*, *30*(24), 4107–4113. http://doi.org/10.1016/1352-2310(96)00176-8

Grosjean, E., & Grosjean, D. (1997). Gas phase reaction of alkenes with ozone: Formation yields of primary carbonyls and biradicals. *Environmental Science & Technology*, *31*(8), 2421–2427. http://doi.org/10.1021/es970075b

Gryparis, A., Forsberg, B., Katsouyanni, K., Analitis, A., Touloumi, G., Schwartz, J., … Dortbudak, Z. (2004). Acute effects of ozone on mortality from the "Air pollution and health: A European approach" project. *American Journal of Respiratory and Critical Care Medicine*, *170*(10), 1080–1087. http://doi.org/10.1164/rccm.200403-333OC

Gundel, Lara A., Sullivan, Douglas P., Katsapov, Gregory Y., & Fisk, William J. (2002). *A pilot study of energy efficient air cleaning for ozone* (No. DE-AC03-76SF00098). Berkeley, CA 94720: Lawrence Berkeley National Laboratory.

Hantula, D. A., Rajala, A. K., Kellerman, E. G. B., & Bragger, J. L. D. (2001). The value of workplace safety: A time-based utility analysis model. *Journal of Organizational Behavior Management*, *21*(2), 79–98. http://doi.org/10.1300/J075v21n02_09

Heisig, C., Zhang, W. M., & Oyama, S. T. (1997). Decomposition of ozone using carbon-supported metal oxide catalysts. *Applied Catalysis B-Environmental*, *14*(1-2), 117–129. http://doi.org/10.1016/S0926-3373(97)00017-9

Henke, R. M., Carls, G. S., Short, M. E., Pei, X., Wang, S., Moley, S., Goetzel, R. Z. (2010). The relationship between health risks and health and productivity costs among employees at Pepsi bottling group. *Journal of Occupational and Environmental Medicine*, *52*(5), 519–527. http://doi.org/10.1097/JOM.0b013e3181dce655

Hodgson, A. T., & Levin, H. (2003, April 21). Volatile Organic Compounds in Indoor Air: A Review of Concentrations Measured in North America Since 1990. Lawrence Berkeley National Laboratory, Berkeley, California, USA Report LBNL-51715.

Hoek, G., Boogaard, H., Knol, A., De Hartog, J., Slottje, P., Ayres, J. G., … Van der Sluijs, J. (2010). Concentration Response Functions for Ultrafine Particles and All-Cause Mortality and Hospital Admissions: Results of a European Expert Panel Elicitation. *Environmental Science & Technology*, *44*(1), 476–482. http://doi.org/10.1021/es9021393

Hubbell, B. J., Hallberg, A., McCubbin, D. R., & Post, E. (2005). Health-related benefits of attaining the 8-hr ozone standard. *Environmental Health Perspectives*, *113*(1), 73–82.

Huijbregts, M. A. J., Rombouts, L. J. A., Ragas, A. M. J., & Meent, D. van de. (2005). Human-Toxicological Effect and Damage Factors of Carcinogenic and Noncarcinogenic Chemicals for Life Cycle Impact Assessment. *Integrated Environmental Assessment and Management*, *1*(3), 181–244.

Hun, D. E., Corsi, R. L., Morandi, M. T., & Siegel, J. A. (2010). Formaldehyde in residences: long-term indoor concentrations and influencing factors. *Indoor Air*, *20*(3), 196–203. http://doi.org/10.1111/j.1600-0668.2010.00644.x

IBM Corporation. (2013). IBM SPSS Statistics (Version 22.0). Armonk, NY.

Ito, K., De Leon, S. F., & Lippmann, M. (2005). Associations between ozone and daily mortality - Analysis and meta-analysis. *Epidemiology*, *16*(4), 446–457. http://doi.org/10.1097/01.ede.0000165821.90114.7f

Jerrett, M., Burnett, R. T., Pope, C. A., Ito, K., Thurston, G., Krewski, D., … Thun, M. (2009). Long-Term Ozone Exposure and Mortality. *New England Journal of Medicine*, *360*(11), 1085–1095. http://doi.org/10.1056/NEJMoa0803894

Kelly, T., & Kinkead, D. (1993). Testing of Chemically Treated Adsorbent Air Purifiers. *Ashrae Journal-American Society of Heating Refrigerating and Air-Conditioning Engineers*, *35*(7), 14–23.

Kelly, E., Carls, G. S., Lenhart, G., Mauceri, E., Columbus, D., Cavuoti, A., & Goetzel, R. Z. (2010). The Novartis Health Index: A method for valuing the economic impact of risk reduction in a workforce. *Journal of Occupational and Environmental Medicine*, *52*(5), 528–535. http://doi.org/10.1097/JOM.0b013e3181dbe339

Kim, S. Y., Lee, J. T., Hong, Y. C., Ahn, K. J., & Kim, H. (2004). Determining the threshold effect of ozone on daily mortality: an analysis of ozone and mortality in Seoul, Korea, 1995-1999. *Environmental Research*, *94*(2), 113–119. http://doi.org/10.1016/j.envres.2003.09.006

Kleno, J., & Wolkoff, P. (2004). Changes in eye blink frequency as a measure of trigeminal stimulation by exposure to limonene oxidation products, isoprene oxidation products and nitrate radicals. *International Archives of Occupational and Environmental Health*, *77*(4), 235–243. http://doi.org/10.1007/s00420-003-0502-1

Klepeis, N. E., Nelson, W. C., Ott, W. R., Robinson, J. P., Tsang, A. M., Switzer, P., … Engelmann, W. H. (2001). The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. *Journal of Exposure*

Analysis and Environmental Epidemiology, *11*(3), 231–252. http://doi.org/10.1038/sj.jea.7500165

Lamble, S. P., Corsi, R. L., & Morrison, G. C. (2011). Ozone deposition velocities, reaction probabilities and product yields for green building materials. *Atmospheric Environment*, *45*(38), 6965–6972. http://doi.org/10.1016/j.atmosenv.2011.09.025

Lawrence Berkeley National Laboratory Center for Building Science Applications Team. (2003, August). A Design Guide for Energy-Efficient Research Laboratories. Retrieved March 9, 2013, from http://ateam.lbl.gov/Design-Guide/index.htm

(LBNL) Lawrence Berkeley National Laboratory. (2014). Home Energy Saver. Retrieved November 18, 2014, from https://sites.google.com/a/lbl.gov/hes-public/page-archive/appendices/appendix-c

Lee, A., Goldstein, A. H., Keywood, M. D., Gao, S., Varutbangkul, V., Bahreini, R., … Seinfeld, J. H. (2006). Gas-phase products and secondary aerosol yields from the ozonolysis of ten different terpenes. *Journal of Geophysical Research-Atmospheres*, *111*(D7). http://doi.org/10.1029/2005JD006437

Lee, A., Goldstein, A. H., Kroll, J. H., Ng, N. L., Varutbangkul, V., Flagan, R. C., & Seinfeld, J. H. (2006). Gas-phase products and secondary aerosol yields from the photooxidation of 16 different terpenes. *Journal of Geophysical Research-Atmospheres*, *111*(D17). http://doi.org/10.1029/2006JD007050

Lee, K., Vallarino, J., Dumyahn, T., Ozkaynak, H., & Spengler, J. D. (1999). Ozone decay rates in residences. *Journal of the Air & Waste Management Association*, *49*(10), 1238–1244.

Lee, P., & Davidson, J. (1999). Evaluation of activated carbon filters for removal of ozone at the PPB level. *American Industrial Hygiene Association Journal*, *60*(5), 589–600. http://doi.org/10.1080/00028899908984478

Leungsakul, S., Jaoui, M., & Kamens, R. M. (2005). Kinetic mechanism for predicting secondary organic aerosol formation from the reaction of d-limonene with ozone. *Environmental Science & Technology*, *39*(24), 9583–9594. http://doi.org/10.1021/es0492687

Levy, J. I., Carrothers, T. J., Tuomisto, J. T., Hammitt, J. K., & Evans, J. S. (2001). Assessing the public health benefits of reduced ozone concentrations. *Environmental Health Perspectives*, *109*(12), 1215–1226. http://doi.org/10.1289/ehp.011091215

Levy, J. I., Chemerynski, S. M., & Sarnat, J. A. (2005). Ozone exposure and mortality - An empiric Bayes metaregression analysis. *Epidemiology*, *16*(4), 458–468. http://doi.org/10.1097/01.ede.0000165820.08301.b3

Lin, Y.-C., Chang, C.-L., Lin, T.-S., Bai, H., Yan, M.-G., Ko, F.-H., … Huang, C.-H. (2008). Application of physical vapor deposition process to modify activated carbon fibers for ozone reduction. *Korean Journal of Chemical Engineering*, *25*(3), 446–450. http://doi.org/10.1007/s11814-008-0076-4

Logue, J. M., McKone, T. E., Sherman, M. H., & Singer, B. C. (2011). Hazard assessment of chemical air contaminants measured in residences. *Indoor Air*, *21*(2), 92–109. http://doi.org/10.1111/j.1600-0668.2010.00683.x

Logue, J. M., Price, P. N., Sherman, M. H., & Singer, B. C. (2012). A Method to Estimate the Chronic Health Impact of Air Pollutants in US Residences. *Environmental Health Perspectives*, *120*(2), 216–222. http://doi.org/10.1289/ehp.1104035

Loh, M. M., Levy, J. I., Spengler, J. D., Houseman, E. A., & Bennett, D. H. (2007). Ranking cancer risks of organic hazardous air pollutants in the United States. *Environmental Health Perspectives*, *115*(8), 1160–1168. http://doi.org/10.1289/ehp.9884

Lopez, A. D., Mathers, C. D., Ezzati, M., Jamison, D. T., & Murray, C. J. L. (2006). *Global Burden of Disease and Risk Factors*. World Bank.

Lvovsky, K., Hughes, G., Maddison, D., Ostro, B., & Pearce, D. (2000). *Environmental Costs of Fossil Fuels* (Environment Department Papers No. Paper No. 78) (pp. 1–104). Washington, DC: World Bank.

MathWorks (2013). MATLAB release 2013a, student edition. Natick, MA.

McConnell, R., Berhane, K., Gilliland, F., London, S. J., Islam, T., Gauderman, W. J., … Peters, J. M. (2002). Asthma in exercising children exposed to ozone: a cohort study. *Lancet*, *359*(9304), 386–391. http://doi.org/10.1016/S0140-6736(02)07597-9

McDonnell, W. F., Abbey, D. E., Nishino, N., & Lebowitz, M. D. (1999). Long-term ambient ozone concentration and the incidence of asthma in nonsmoking adults: The ahsmog study. *Environmental Research*, *80*(2), 110–121. http://doi.org/10.1006/enrs.1998.3894

Metts, T. A. (2007). Heterogeneous reactions of ozone and D-limonene on activated carbon. *Indoor Air*, *17*(5), 362–371. http://doi.org/10.1111/j.1600-0668.2007.00484.x

Metts, T. A., & Batterman, S. A. (2006). Effect of VOC loading on the ozone removal efficiency of activated carbon filters. *Chemosphere*, *62*(1), 34–44. http://doi.org/10.1016/j.chemosphere.2005.04.049

Moolgavkar, S. H., Luebeck, E. G., & Anderson, E. L. (1997). Air pollution and hospital admissions for respiratory causes in Minneapolis St. Paul and Birmingham. *Epidemiology*, *8*(4), 364–370. http://doi.org/10.1097/00001648-199707000-00003

Morrison, G. C., & Nazaroff, W. W. (2002). Ozone interactions with carpet: Secondary emissions of aldehydes. *Environmental Science & Technology*, *36*(10), 2185–2192. http://doi.org/10.1021/es0113089

Morrison, G. C., Nazaroff, W. W., Cano-Ruiz, J. A., Hodgson, A. T., & Modera, M. P. (1998). Indoor air quality impacts of ventilation ducts: Ozone removal and emissions of volatile organic compounds. *Journal of the Air & Waste Management Association*, *48*(10), 941–952.

Morrison, G., Shaughnessy, R., & Shu, S. (2011). Setting maximum emission rates from ozone emitting consumer appliances in the United States and Canada. *Atmospheric Environment*, *45*(11), 2009–2016. http://doi.org/10.1016/j.atmosenv.2010.11.058

Mudway, I. S., & Kelly, F. J. (2004). An investigation of inhaled ozone dose and the magnitude of airway inflammation in healthy adults. *American Journal of Respiratory and Critical Care Medicine*, *169*(10), 1089–1095. http://doi.org/10.1164/rccm.200309-13251-1325PP

Muller, C. O., & Jin, L. (2009). Beyond Ozone: Cleaning Outdoor Air for Improved IAQ. In X. S. Zhang, H. Qian, B. Zhou, & Y. G. Yin (Eds.), . Presented at the 6th International

Symposium on Heating, Ventilation, and Air Conditioning, Vols I-III, Proceedings, Nanjing, Peoples Republic of China.

Musich, S., McCalister, T., Wang, S., & Hawkins, K. (2015). An evaluation of the Well at Dell health management program: health risk change and financial return on investment. *American Journal of Health Promotion*, *29*(3), 147–157. http://doi.org/10.4278/ajhp.131115-QUAN-582

Nazaroff, W. W., Coleman, B. K., Destaillats, H., Hodgson, A. T., Liu, D.-L., Lunden, M. M., Weschler, C. J. (2006). *Indoor Air Chemistry: Cleaning Agents, Ozone and Toxic Air Contaminants* (No. California Air Resources Boad Contract No. 01-336). Lawrence Berkeley National Laboratory.

Nazaroff, W. W., & Singer, B. C. (2004). Inhalation of hazardous air pollutants from environmental tobacco smoke in US residences. *Journal of Exposure Analysis and Environmental Epidemiology*, *14*, S71–S77. http://doi.org/10.1038/sj.jea.7500361

Nazaroff, W. W., & Weschler, C. J. (2004). Cleaning products and air fresheners: exposure to primary and secondary air pollutants. *Atmospheric Environment*, *38*(18), 2841–2865. http://doi.org/10.1016/j.atmosenv.2004.02.040

Ng, N. L., Kroll, J. H., Keywood, M. D., Bahreini, R., Varutbangkul, V., Flagan, R. C., … Goldstein, A. H. (2006). Contribution of first- versus second-generation products to secondary organic aerosols formed in the oxidation of biogenic hydrocarbons. *Environmental Science & Technology*, *40*(7), 2283–2297. http://doi.org/10.1021/es052269u

Oberdorster, G., Elder, A., Finkelstein, J., Frampton, M., Hopke, P., Peters, A., … Utell, M. (2010). *Assessment of Ambient UFP Health Effects:Linking Sources to Exposure and Responses in Extrapulmonary Organs* (No. EPA Grant R827354). University of Rochester.

Office of Environmental Health Hazard Assessment (OEHHA). (2008). *Air Toxics Hot Spots Program Risk Assessment Guidelines. Technical Support Document for the Derivation of Noncancer Reference Exposure Levels*. California Environmental Protection Agency.

Ostro, B., & Rothschild, S. (1989). Air-Pollution and Acute Respiratory Morbidity - An Observational Study. *Environmental Research*, *50*(2), 238–247. http://doi.org/10.1016/S0013-9351(89)80004-0

Parodi, S., Vercelli, M., Garrone, E., Fontana, V., & Izzotti, A. (2005). Ozone air pollution and daily mortality in Genoa, Italy between 1993 and 1996. *Public Health*, *119*(9), 844–850. http://doi.org/10.1016/j.puhe.2004.10.007

Persily, A., Musser, A., & Emmerich, S. J. (2010). Modeled infiltration rate distributions for U.S. housing. *Indoor Air*, *20*(6), 473–485. http://doi.org/10.1111/j.1600-0668.2010.00669.x

Polidori, A., Arhami, M., Sioutas, C., Delfino, R. J., & Allen, R. (2007). Indoor/outdoor relationships, trends, and carbonaceous content of fine particulate matter in retirement homes of the Los Angeles basin. *Journal of the Air & Waste Management Association*, *57*(3), 366–379.

Pope, C. A., Burnett, R. T., Turner, M. C., Cohen, A., Krewski, D., Jerrett, M., … Thun, M. J. (2011). Lung Cancer and Cardiovascular Disease Mortality Associated with Ambient Air

Pollution and Cigarette Smoke: Shape of the Exposure-Response Relationships. *Environmental Health Perspectives*, *119*(11), 1616–1621. http://doi.org/10.1289/ehp.1103639

Rascati, K. (2009). *Essentials of Pharmacoeconomics*. Baltimore, MD: Lippincott, Williams, and Wilkins.

Reiss, R., Ryan, P., Koutrakis, P., & Tibbetts, S. (1995). Ozone Reactive Chemistry on Interior Latex Paint. *Environmental Science & Technology*, *29*(8), 1906–1912. http://doi.org/10.1021/es00008a007

Richard Corsi, Josh Aldred, Erin Darling, Glenn Morrison, & Jeffrey Siegel. (2014). *Literature and Product Review and Cost Benefit Analysis of Commercially Available Ozone Air Cleaning for HVAC Systems* (No. Research Project 1491). Austin, TX: American Society of Heating, Refrigeration, and Air Conidtioning Engineers.

Rohr, A. C., Shore, S. A., & Spengler, J. D. (2003). Repeated exposure to isoprene oxidation products causes enhanced respiratory tract effects in multiple murine strains. *Inhalation Toxicology*, *15*(12), 1191–1207. http://doi.org/10.1080/08958370390229870

Rohr, A. C., Weschler, C. J., Koutrakis, P., & Spengler, J. D. (2003). Generation and quantification of ultrafine particles through terpene/ozone reaction in a chamber setting. *Aerosol Science and Technology*, *37*(1), 65–78. http://doi.org/10.1080/02786820390112597

Rosenthal, J. (2014, April). Correspondence with J. Aldred. Austin, TX.

Sabersky, R., Sinema, D., & Shair, F. (1973). Concentrations, Decay Rates, and Removal of Ozone and Their Relation to Establishing Clean Indoor Air. *Environmental Science & Technology*, *7*(4), 347–353. http://doi.org/10.1021/es60076a001

Sarnat, J. A., Brown, K. W., Schwartz, J., Coull, B. A., & Koutrakis, P. (2005). Ambient gas concentrations and personal particulate matter exposures - Implications for studying the health effects of particles. *Epidemiology*, *16*(3), 385–395. http://doi.org/10.1097/01.ede.0000155505.04775.33

Sarnat, J. A., Schwartz, J., Catalano, P. J., & Suh, H. H. (2001). Gaseous pollutants in particulate matter epidemiology: Confounders or surrogates? *Environmental Health Perspectives*, *109*(10), 1053–1061. http://doi.org/10.2307/3454961

Sarwar, G., & Corsi, R. (2007). The effects of ozone/limonene reactions on indoor secondary organic aerosols. *Atmospheric Environment*, *41*(5), 959–973. http://doi.org/10.1016/j.atmosenv.2006.09.032

Sarwar, G., Corsi, R., Allen, D., & Weschler, C. (2003). The significance of secondary organic aerosol formation and growth in buildings: experimental and computational evidence. *Atmospheric Environment*, *37*(9-10), 1365–1381. http://doi.org/10.1016/S1352-2310(02)01013-0

Sax, S. N., Bennett, D. H., Chillrud, S. N., Ross, J., Kinney, P. L., & Spengler, J. D. (2006). A cancer risk assessment of inner-city teenagers living in New York City and Los Angeles. *Environmental Health Perspectives*, *114*(10), 1558–1566. http://doi.org/10.1289/ehp.8507

SCAQMD (South Coast Air Quality Management District). (2013). Historic Ozone Air Quality Trends. Retrieved January 11, 2013, from http://www.aqmd.gov/smog/O3trend.html.

Scheuer, C., Keoleian, G. A., & Reppe, P. (2003). Life cycle energy and environmental performance of a new university building: modeling challenges and design implications. *Energy and Buildings*, *35*(10), 1049–1064. http://doi.org/10.1016/S0378-7788(03)00066-5

Schwartz, S. M., Mason, S. T., Wang, C., Pomana, L., Hyde-Nolan, M. E., & Carter, E. W. (2014). Sustained economic value of a wellness and disease prevention program: an 8-year longitudinal evaluation. *Population Health Management*, *17*(2), 90–99. http://doi.org/10.1089/pop.2013.0042

Shair, F. H. (1981). Relating Indoor Pollutant Concentrations of Ozone and Sulfur Dioxide to those Outside: Economic Reduction of Indoor Ozone through Selective Filtration of the Make- Up Air. *ASHRAE Transactions*, *87*, 116–139.

Shields, H. C., Weschler, C. J., & Naik, D. (1999). Ozone Removal by Charcoal Filters after Continuous Extensive Use (5 to 8 years). In *Proceedings of the 8th International Conference on Indoor Air Quality and Climate* (Vol. 4, pp. 49–54).

Singer, B. C., Destaillats, H., Hodgson, A. T., & Nazaroff, W. W. (2006). Cleaning products and air fresheners: emissions and resulting concentrations of glycol ethers and terpenoids. *Indoor Air*, *16*(3), 179–191. http://doi.org/10.1111/j.1600-0668.2005.00414.x

Slob, W. (1994). Uncertainty Analysis in Multiplicative Models. *Risk Analysis*, *14*(4), 571–576. http://doi.org/10.1111/j.1539-6924.1994.tb00271.x

Smith, R. L., Xu, B., & Switzer, P. (2009). Reassessing the relationship between ozone and short-term mortality in. *Inhalation Toxicology*, *21*, 37–61. http://doi.org/10.1080/08958370903161612

Spadaro, J. V., & Rabl, A. (2008). Estimating the uncertainty of damage costs of pollution: A simple transparent method and typical results. *Environmental Impact Assessment Review*, *28*(2-3), 166–183. http://doi.org/10.1016/j.eiar.2007.04.001

Stanley, W. B. M., Ligman, B. K., Rahmathullah, M. A., & Nance, N. J. (2011). Life Cycle Valuation of Gas-Phase Filters for Ozone Removal. Presented at the The 12th International Conference of Indoor Air Quality and Climate, Austin, TX.

Stephens, B., Gall, E. T., & Siegel, J. A. (2012). Measuring the Penetration of Ambient Ozone into Residential Buildings. *Environmental Science & Technology*, *46*(2), 929–936. http://doi.org/10.1021/es2028795

Stephens, B., Siegel, J. A., & Novoselac, A. (2011). Operational characteristics of residential and light-commercial air-conditioning systems in a hot and humid climate zone. *Building and Environment*, *46*(10), 1972–1983. http://doi.org/10.1016/j.buildenv.2011.04.005

Stevens, J. (2014). Topical Review: Behavioral Economics as a Promising Framework for Promoting Treatment Adherence to Pediatric Regimens. *Journal of Pediatric Psychology*, *39*(10), 1097–1103. http://doi.org/10.1093/jpepsy/jsu071

Tager, I. B., Balmes, J., Lurmann, F., Ngo, L., Alcorn, S., & Kunzli, N. (2005). Chronic exposure to ambient ozone and lung function in young adults. *Epidemiology*, *16*(6), 751–759. http://doi.org/10.1097/01.ede.0000183166.68809.b0

Takeuchi, Y., & Itoh, T. (1993). Removal of Ozone From Air by Activated Carbon Treatment. *Separations Technology*, *3*(3), 168–175. http://doi.org/10.1016/0956-9618(93)80017-L

TCEQ. (2014, March 18). Air Quality Data and Evaluations. Retrieved November 1, 2014, from http://www.tceq.state.tx.us/agency/data/aq-data.html

Thurston, G. D., & Ito, K. (2001). Epidemiological studies of acute ozone exposures and mortality. *Journal of Exposure Analysis and Environmental Epidemiology*, *11*(4), 286–294. http://doi.org/10.1038/sj.jea.7500169

Turner, M. C., Krewski, D., Pope, C. A., Chen, Y., Gapstur, S. M., & Thun, M. J. (2011). Long-term Ambient Fine Particulate Matter Air Pollution and Lung Cancer in a Large Cohort of Never-Smokers. *American Journal of Respiratory and Critical Care Medicine*, *184*(12), 1374–1381. http://doi.org/10.1164/rccm.201106-1011OC

Tversky, A., & Kahneman, D. (1992). Advances in Prospect-Theory - Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. http://doi.org/10.1007/BF00122574

U.S. Bureau of Labor Statistics. (2014, November). CPI Inflation Calculator. Retrieved November 20, 2014, from http://data.bls.gov/cgi-bin/cpicalc.pl

US Census Bureau. (2012, April). Households and Families: 2010. Retrieved August 20, 2013, from http://www.census.gov/prod/cen2010/briefs/c2010br-14.pdf

US Census Bureau. (2013a). Texas Cities Lead Nation in Population Growth, Census Bureau Reports - Population - Newsroom - U.S. Census Bureau. Retrieved February 4, 2014, from http://www.census.gov/newsroom/releases/archives/population/cb13-94.html

US Census Bureau. (2013b, July 24). American Housing Survey. Retrieved September 20, 2013, from http://www.census.gov/housing/ahs/

USDOE (U.S. Department of Energy). (2012). Commercial Prototype Building Models. Retrieved January 14, 2014, from http://www.energycodes.gov/development/commercial/90.1_models

U.S. Energy Information Administration. (2013, August 7). Commercial Building Energy Consumption Survey. Retrieved September 20, 2013, from http://www.eia.gov/consumption/commercial/

U.S. Energy Information Administration. (2014a, June 18). How much energy is consumed in residential and commercial buildings in the United States? Retrieved from http://www.eia.gov/tools/faqs/faq.cfm?id=86&t=1

U.S. Energy Information Administration. (2014b, October). Electric Power Monthly. Retrieved November 18, 2014, from http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_5_6_b

USEPA. (2006). *Air Quality Criteria for Ozone and Related Photochemical Oxidants* (No. EPA/600/R-05/004aF-cF). Washington, DC: U.S. Environmental Protection Agency.

USEPA. (2008). *Final Ozone NAAQS Regulatory Impact Analysis* (No. EPA-452/R-08-003). Research Triangle Park, NC.

USEPA. (2010). *Quantitative Health Risk Assessment for Particulate Matter* (No. EPA-452/R-10-005) (pp. 1–531). Research Triangle Park, NC. Retrieved from http://www.epa.gov/ttnnaaqs/standards/pm/data/20100209RA2ndExternalReviewDraft.pdf

USEPA. (2011a). *Integrated Science Assessment of Ozone and Related Photochemical Oxidants (First External Review Draft)* (No. EPA/600/R-10/076A). Washington, DC: U.S. Environmental Protection Agency.

USEPA. (2011b). *Regulatory Impact Analysis Final National Ambient Air Quality Standard for Ozone*. Research Triangle Park, NC.

USEPA. (2011c). *The Benefits and Costs of the Clean Air Act from 1990 to 2020 - Final Report*. Washington, DC: U.S. Environmental Protection Agency.

USEPA. (2012, November 28). National Trends in Ozone Levels. Retrieved January 11, 2013, from http://www.epa.gov/airtrends/ozone.html

USEPA. (2013a, January 17). EPA AirData. Retrieved September 20, 2013, from https://ofmext.epa.gov/AQDMRS/aqdmrs.html

USEPA. (2013b, August 15). 8-Hour Ozone Nonattainment Areas. Retrieved December 18, 2013, from http://www.epa.gov/oaqps001/greenbk/map8hr.html

USEPA. (2013c, September 3). Air Trends - Ozone. Retrieved September 23, 2013, from http://www.epa.gov/airtrends/ozone.html#oznat

USEPA. (2014a). *Regulatory Impact Analysis of the Proposed Revisions to the National Ambient Air Quality Standards for Ground-Level Ozone* (No. EPA-452/P-14-006). Research Triangle Park, NC.

USEPA. (2014b, July). Summary Nonattainment Area Population Exposure Report. Retrieved November 20, 2014, from http://www.epa.gov/airquality/greenbook/popexp.html

USEPA. (n.d.). Integrated Risk Information System (IRIS) [Reports & Assessments]. Retrieved November 1, 2014, from http://www.epa.gov/IRIS/

USEPA -- Office of Air Quality Planning and Standards. (2012). *BenMAP - Environmental Benefits Mapping and Analysis Program - User's Manual Appendices*.

U.S. Green Buildings Council. (2014). USGBC Headquarters Scorecard. Retrieved from http://www.usgbc.org/projects/usgbc-headquarters?view=scorecard

Wang, H., & Morrison, G. (2010). Ozone-surface reactions in five homes: surface reaction probabilities, aldehyde yields, and trends. *Indoor Air*, *20*(3), 224–234. http://doi.org/10.1111/j.1600-0668.2010.00648.x

Wang, H., & Morrison, G. C. (2006). Ozone-initiated secondary emission rates of aldehydes from indoor surfaces in four homes. *Environmental Science & Technology*, *40*(17), 5263–5268. http://doi.org/10.1021/es060080s

Wargocki, P., & Djukanovic, R. (2005). Simulations of the potential revenue from investment in improved indoor air quality in an office building. *ASHRAE Transactions*, *111*.

Weisel, C. P., Zhang, J. (Jim), Turpin, B. J., Morandi, M. T., Colome, S., Stock, T. H., & Spektor, D. M. (2005). *Relationships of Indoor, Outdoor, and Personal Air (RIOPA) Part I. Collection Methods and Descriptive Analyses* (130 Part 1). Health Effects Institute.

Weschler, C. J. (2000). Ozone in indoor environments: Concentration and chemistry. *Indoor Air-International Journal of Indoor Air Quality and Climate*, *10*(4), 269–288. http://doi.org/10.1034/j.1600-0668.2000.010004269.x

Weschler, C. J. (2004). Chemical reactions among indoor pollutants: what we've learned in the new millennium. *Indoor Air*, *14*, 184–194. http://doi.org/10.1111/j.1600-0668.2004.00287.x

Weschler, C. J. (2006). Ozone's impact on public health: Contributions from indoor exposures to ozone and products of ozone-initiated chemistry. *Environmental Health Perspectives*, *114*(10), 1489–1496. http://doi.org/10.1289/ehp.9256

Weschler, C. J., & Shields, H. C. (1996). Production of the hydroxyl radical in indoor air. *Environmental Science & Technology*, *30*(11), 3250–3258. http://doi.org/10.1021/es960032f

Weschler, C. J., & Shields, H. C. (1999). Indoor ozone/terpene reactions as a source of indoor particles. *Atmospheric Environment*, *33*(15), 2301–2312. http://doi.org/10.1016/S1352-2310(99)00083-7

Weschler, C. J., & Shields, H. C. (2000). The influence of ventilation on reactions among indoor pollutants: Modeling and experimental observations. *Indoor Air-International Journal of Indoor Air Quality and Climate*, *10*(2), 92–100. http://doi.org/10.1034/j.1600-0668.2000.010002092.x

Weschler, C. J., Wells, J. R., Poppendieck, D., Hubbard, H., & Pearce, T. A. (2006). Workgroup report: Indoor chemistry and health. *Environmental Health Perspectives*, *114*(3), 442–446. http://doi.org/10.1289/ehp.8271

Wilcox, S., & Marion, W. (2008). *User's Manual for TMY3 Data Sets* (No. NREL/TP-581-43156). Golden, Colorado: National Renewable Energy Laboratory.

Wisthaler, A., & Weschler, C. J. (2010). Reactions of ozone with human skin lipids: Sources of carbonyls, dicarbonyls, and hydroxycarbonyls in indoor air. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(15), 6568–6575. http://doi.org/10.1073/pnas.0904498106

Wolkoff, P., Clausen, P. A., Larsen, K., Hammer, M., Larsen, S. T., & Nielsen, G. D. (2008). Acute airway effects of ozone-initiated d-limonene chemistry: Importance of gaseous products. *Toxicology Letters*, *181*(3), 171–176. http://doi.org/10.1016/j.toxlet.2008.07.018

Wolkoff, P., Clausen, P. A., Larsen, S. T., Hammer, M., & Nielsen, G. D. (2012). Airway effects of repeated exposures to ozone-initiated limonene oxidation products as model of indoor air mixtures. *Toxicology Letters*, *209*(2), 166–172. http://doi.org/10.1016/j.toxlet.2011.12.008

Wolkoff, P., Clausen, P. A., Wilkins, C. K., Hougaard, K. S., & Nielsen, G. D. (1999). Formation of strong airway irritants in a model mixture of (+)-alpha-pinene/ozone. *Atmospheric Environment*, *33*(5), 693–698. http://doi.org/10.1016/S1352-2310(98)00292-1

Wolkoff, P., Clausen, P. A., Wilkins, C. K., & Nielsen, G. D. (2000). Formation of strong airway irritants in terpene/ozone mixtures. *Indoor Air*, *10*(2), 82–91. http://doi.org/10.1034/j.1600-0668.2000.010002082.x

Wolkoff, P., & Nielsen, G. D. (2010). Non-cancer effects of formaldehyde and relevance for setting an indoor air guideline. *Environment International*, *36*(7), 788–799. http://doi.org/10.1016/j.envint.2010.05.012

World Bank. (2014, November). World Bank Economic Data. Retrieved November 20, 2014, from http://data.worldbank.org/country/united-states#cp_wdi

Yang, Q. Y., Chen, Y., Shi, Y. L., Burnett, R. T., McGrail, K. M., & Krewski, D. (2003). Association between ozone and respiratory admissions among children and the elderly in Vancouver, Canada. *Inhalation Toxicology*, *15*(13), 1297–1308. http://doi.org/10.1080/08958370390241768

Youssefi, S., & Waring, M. S. (2012). Predicting secondary organic aerosol formation from terpenoid ozonolysis with varying yields in indoor environments. *Indoor Air*, *22*(5), 415–426. http://doi.org/10.1111/j.1600-0668.2012.00776.x

Zhang, L., Tang, X., Rothman, N., Vermeulen, R., Ji, Z., Shen, M., … Lan, Q. (2010). Occupational Exposure to Formaldehyde, Hematotoxicity, and Leukemia-Specific Chromosome Changes in Cultured Myeloid Progenitor Cells. *Cancer Epidemiology Biomarkers & Prevention*, *19*(1), 80–88. http://doi.org/10.1158/1055-9965.EPI-09-0762

Zhang, Y., Huang, W., London, S. J., Song, G., Chen, G., Jiang, L., … Kan, H. (2006). Ozone and daily mortality in Shanghai, China. *Environmental Health Perspectives*, *114*(8), 1227–1232. http://doi.org/10.1289/ehp.9014

Vita

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